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INSTITUTIONAL TRADING AND STOCK PRICE EFFICIENCY

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INSTITUTIONAL TRADING AND STOCK PRICE EFFICIENCY

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INSTITUTIONAL TRADING AND STOCK PRICE EFFICIENCY

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My dissertation finds that the effects of institutional trading on stock price efficiency are significant and complicated. On one hand, I present evidence that institutional trading in general improves price efficiency. In particular, major stock market anomalies such as stock return momentum, post earnings announcement drift, and the book-to-market effect are much stronger in stocks with lower institutional trading volume. On the other, some institutional trading behaviors could hamper stock price efficiency even though institutions are generally rational arbitrageurs. Specifically, I show that when institutions act as positive-feedback traders, their trading contributes to stock return momentum and hampers prices efficiency.

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The dramatic growth of institutional investors is one of the most important phenomena in the US stock market during the past three decades. For example, institutional ownership of US common equities increased from 16% in 1965 to over 61% in 2002. Such rapid growth has motivated numerous studies on institutions investors. For example, many paper study the influence of institutional investors on various stock market phenomena such as January anomaly, size premium, post earnings-announcement drift, short sales constraint, high tech bubble, etc.[1] Other papers examine how institutional investors affect corporate events including shareholder activism, management compensation, CEO turnover, dividend policy, etc.[2]

How does institutional trading affect stock price efficiency? If institutions have information advantage and act as 'rational arbitrageurs', then institutions could improve stock market efficiency. Since institutions have become the most important investors in the stock market, this research question is very interesting and important. It not only helps academic researchers understand the dynamics of market efficiency but also help practitioners search for potential profitable trading strategies.

Previous studies provide mixed evidence on the effects of institutional trading on price efficiency. On one hand, some researchers show that institutions have information advantage and therefore improve price efficiency. For example, Nofsinger and Sias (1999) find that change in institutional ownership is positively related to both contemporaneous and subsequent stock returns. Alangar, Bathala, and Rao (1999) document weaker price response to dividend-change announcement for high institutional ownership firms. In

[1]See, for example, Sias and Starks (1997), Gompers and Metrick (2001), Ng and Wang (2004), Nofsinger and Sias (1999), Nagel (2005), Brunnermeier and Nagel (2004), etc.

[2]See, for example, Parrino, Sias, and Starks (2003), Hartzell and Starks (2003), Gillan and Starks (2000), Grinstein and Michaely (2005), etc.

addition, Bartov, Radhakrishnan, and Krinsky (2000) observe weaker post-earnings announcement drift for firms with higher institutional ownership. Cohen, Gompers, and Vuolteenaho (2002) show that institutions purchase stocks with positive cash flow news. Irvine, Lipson, and Puckett (2007) reveal that institutions have access to analyst recommendations before they are publicly released.

However, other studies build cases where institutions do not have information advantage or their trading hampers price efficiency. For example Brunnermeier and Nagel (2004) analyze hedge fund trades during high tech bubble and find that hedge funds rode the bubble rather than attacking it. A recent study by Frazzini (2005) also document that disposition effect causes mutual funds' sub-optimal trading behavior which intensifies post earnings-announcement drift. In addition, there is a huge literature debating on whether mutual funds managers have superior information or stock picking skills. [3]

My dissertation shows that the effects of institutional trading on stock price efficiency are significant and complicated. Specifically, I find evidence that institutional trading in general improves price efficiency, but particular institutional trading behavior could nevertheless hamper stock price efficiency. My dissertation presents results from two aspects: 1) Consistent with institutional trading improving overall price efficiency, I find that stock market anomalies, such as return momentum, post earnings-announcement

[3] See, for example, Grinblatt and Titman (1992), Brown, Goetzmann, Ibbotson, and Ross (1992), Grinblatt and Titman (1993), Grinblatt and Titman (1994), Malkiel (1995), Ferson and Schadt (1996), Daniel, Grinblatt, Titman, and Wermers (1997), Carhart (1997), Dahlquist and Soderlind (1999), Wermers (1999), Wermers (2000), Bollen and Busse (2001), Carhart, Carpenter, Lynch, and Musto (2002), Pastor and Stambaugh (2002b), Pastor and Stambaugh (2002a), Cohen, Coval, and Pastor (2005), Chen, Jegadeesh, and Wermers (2000), Baks, Metrick, and Wachter (2001), etc.

drift, and the value premium are much stronger in stocks with lower fractions of institutional trading volume. In addition, stocks with lower fractions of institutional trading volume underperform stocks with higher fractions. 2) I find that when institutions act as positive-feedback traders, their positive-feedback trading contributes to stock return momentum and hampers price efficiency.

The first chapter examines the effect of trader composition on price efficiency and therefore the cross-section of stock returns, where I evaluate trader composition with the fraction of institutional trading volume in the total trading volume of a stock. Trader composition of a stock could differ substantially from its institutional ownership because shareholders are not necessarily traders. If, for example, pension funds with a long investment horizon hold 90% of a stock's shares but rarely trade, then the stock could have a low percentage of institutional trading volume despite high institutional ownership. Similarly, a stock could have low institutional ownership but be traded actively by institutions if a group of hedge funds or active mutual funds own the security.

If institutions tend to be better informed and more sophisticated than individuals, then higher fractions of institutional trading volume could lead to greater price efficiency through two channels. First, active institutional trading could help incorporate information into stock prices rapidly. Holden and Subrahmanyam (1992), for example, show that aggressive competition between informed traders could facilitate the information revelation process. Moreover, several previous studies find that institutional trading can move stock prices.[4] As a result, informed institutional trading could speed up the

[4]Chan and Lakonishok (1997), Nofsinger and Sias (1999), Chakravarty (2001), Griffin, Harris, and Topaloglu (2003), and Sias, Starks, and Titman (2006) discuss the price impact

information revelation process and move stocks prices towards their fundamental values.

The second channel through which trader composition affects price efficiency relies on the 'limit of arbitrage' intutition developed by DeLong, Shleifer, Summers, and Waldmann (1990a) and Shleifer and Vishny (1997). When noise traders are prevalent, rational traders will be reluctant to arbitrage away mispricing, since such arbitrage will result in a loss if in the next period noise traders' misconceptions deepen and drive stock prices further away from the fundamental values. Therefore, price efficiency could be lower for stocks traded less by rational traders, in our case, institutional traders.

I first construct a trader composition measure that evaluates the fraction of institutional trading volume in the total trading volume of a stock (henceforth FIT). I further decompose the FIT measure into fraction of institutional buy volume and fraction of institutional sell volume. The average fraction of institutional trading volume is 54% during 1980-2005, including a 28% buy volume and a 25% sell volume. This result suggests that institutions account for over half of the trading volume during 1980-2005.[5]

Trader composition is a new concept in the literature of institutional investors, which is a different concept from change in institutional ownership that is studied by a number of previous studies such as Nofsinger and Sias (1999), Bennett, Sias, and Starks (2003), and Sias, Starks, and Titman (2006). In particular, these studies examine the determinants or influence of change in aggregate institutional ownership (henceforth CIO). Trader composition and CIO are different concepts both economically and empirically.

of institutional trading.

[5]My sample is restricted to NYSE/AMEX firms because the trading volumes of Nasdaq firms are inflated relative to NYSE/AMEX firms.

Economically, CIO is the net change aggregated institutional ownership while trader composition is the fraction of institutional trading volume in the total trading volume. Empirically, CIO is the aggregation of signed change in the ownership across institutions, trader composition is the aggregation of the absolute values of changes in institutional ownership (proxy of trading volume) across institutions and then adjusted by the total trading volume. Empirically, the correlation between the FIT measure and change in institutional ownership is as low as 0.02.

Since trader composition is a new concept, I start with the determinants of trader composition. The results show that both institutional ownership and firm characteristics affect trader composition. However, the most important determinant of a firm's trader composition is its trader composition in the previous period. In other words, trader composition is relatively persistent over time.

I further examine the source of the aforementioned persistence in trader composition and find evidence that it is related to information asymmetry. Two theoretical models by Froot, Scharfstein, and Stein (1992) and Hirshleifer, Subrahmanyam, and Titman (1994) both suggest that when there is information asymmetry and some investors learn information earlier than others, investors will focus on some securities but ignore others with similar characteristics. Therefore, in the presence of informational asymmetry, rational investors, in our case institutional investors, will concentrate their trading in some stocks but ignore others in a period of time, leading to persistent trader composition in this period. Consistent with these two theoretical models, I find that trader composition is more persistent for firms with less analyst coverage, a group associated with non-trivial information asymmetry.

After exploring the determinants of trader composition, I investigate the effects of trader composition on the cross-section of stock returns. I first examine the direct effect of trader composition by testing two competing hypothesis.

On one hand, according to the conclusion of DeLong, Shleifer, Summers, and Waldmann (1990a), one would expect low FIT stocks to outperform high FIT stocks because their paper suggests that stocks heavily traded by noise traders earn higher returns. On the other hand, in the presence of mispricing, low FIT stocks could underperform high FIT stocks if mispricing is concentrated in low FIT stocks and if overpricing is the predominant form of mispricing. Several studies have shown that overpricing is difficult to arbitrage away because correcting overpricing often involves short sales which could be costly or constrained.[6] In addition, the profits of trading strategies employing many stock market anomalies such as price momentum, the value premium, and IPO underperformance come mainly from the short side, which is also supportive of overpricing being the predominant form of mispricing. Therefore low FIT stocks are overpriced and will earn lower returns in the subsequent period.

The empirical results show that low FIT stocks earn *lower* returns, which is consistent with the overpricing hypothesis but inconsistent with DeLong, Shleifer, Summers, and Waldmann (1990a). For example, the bottom FIT decile underperform the top FIT decile by 0.32 to 0.57 percent monthly depending on different risk adjustments.

In addition to the aforementioned direct effect, I further analyze the ef-

[6]See, for example, Geczy, Musto, and Reed (2002), Chen, Hong, and Stein (2002), Almazan, Brown, Carlson, and Chapman (2004), Nagel (2005) and Asquith, Pathak, and Ritter (2005), for the discussion of short sales constraints.

fects of trader composition on stock market anomalies. If low FIT stocks are associated with less price efficiency, then apparent profit opportunities should be stronger in low FIT stocks. Consistently, I find that three major anomalies such as return momentum, post earnings-announcement drift and the value premium (book-to-market effect) are much stronger in low FIT stocks. For example, return momentum is 0.53% per month stronger in the bottom FIT tercile than in the top FIT tercile; post earnings-announcement drift is 0.50% per month stronger; and the value premium is larger by 0.63% per month.[7] These results are robust after controlling for other factors documented to affect these anomalies.

In order to separate the effects of trader composition from those of institutional ownership, I also construct a residual FIT measure (henceforth ResFIT). The ResFIT measure, calculated as residuals from the regressions of FIT on institutional ownership, is orthogonal to institutional ownership. All the aforementioned effects of trader composition are robust with the ResFIT measure.

A contemporaneous paper by Boehmer and Kelley (2006) also observes a positive relationship between fraction of institutional trading volumes and price efficiency. However, my paper differs from Boehmer and Kelley (2006) in several important ways. First, although both papers examine the effect of trader composition, they focus on Hasbrouck (1993)'s price-based efficiency measures while I study the cross-section of stock returns. Second, unlike Boehmer and Kelley (2006), I investigate the determinants of trader com-

[7]Return momentum is monthly profit of six month/six month momentum strategy proposed by Jegadeesh and Titman (1993). Post earnings announcement drift is monthly profit of a six-month rolling PEAD strategy proposed by Frazzini (2005) based on earnings announcement shocks, and the value premium is monthly return difference between the top and bottom decile of the book-to-market ratio.

position to further understand this new conception. Third, Boehmer and Kelley (2006) focus on the short-term effects of trader composition on an intra-day or daily basis while my study examines the intermediate effects of trader composition from one to six months. Last, their study employs a proprietary database which covers a relatively short period from 2000-2003, while my papers examines a much longer period from 1980-2005.

My study is also related to the literature of transient institutions introduced first by Bushee (1998). In particular, Bushee (1998) classifies institutions into transient and non-transient institutions according to how actively they trade. He shows that firms with high ownership by transient institutions tend to cut investment in research and development to meet the short-term earnings goals. Bushee (2001) further find that high transient institutional ownership could motivate various earnings management to boost up short-term earnings. In addition, Collins, Gong, and Hribar (2003) finds that prices of firms with high transient institutional ownerships more accurately reflect the persistence of accruals. These papers provide evidence of the different influences between active and inactive institution investors. While they address this question by examining institutional ownership of active institutions, my paper directly examine the trading volume of institutional investors in the total trading volume. The trader composition measure not only assigns more weight to active institutional investors because they account for more trading volume, but also includes the trading volume of inactive institutional investors, which could also be rational traders in the financial market.

The first chapter presents evidence that institutional trading generally improves price efficiency. However, these findings do not necessarily conclude that institutional trading *always* improves price efficiency. Since institutions are very different in terms of investment goals, investment horizons, and they adopt a wide range of trading strategies, some of their trading patterns could potentially hamper price efficiency even though institutional in general act as rational arbitrageurs. To investigate this possibility, in the second chapter I examine the effect of a particular institutional trading pattern — institutional positive-feedback trading — on stock return momentum and price efficiency.

The second chapter is also motivated by two theoretical studies DeLong, Shleifer, Summers, and Waldmann (1990b) and Hong and Stein (1999) which suggest that positive-feedback trading can produce stock return momentum. Specifically, their models both introduce a group of positive-feedback traders who simply buy when prices rise and sell when prices fall. As a result of the price pressure caused by such positive-feedback trading, stock return momentum is generated. Interestingly, when discussing the identity of the momentum traders in their model, Hong and Stein (1999) claim that "it should be noted that a number of large and presumably sophisticated money managers use what are commonly described as momentum approaches ..."

The second chapter is the first study to empirically show that, consistent with the theoretical models by DeLong, Shleifer, Summers, and Waldmann (1990b) and Hong and Stein (1999), positive-feedback trading by institutions contributes to stock return momentum. In addition, this study further reveals that positive-feedback trading by institutions destabilizes stock prices and hence hampers market efficiency.

Despite the heavy empirical literature on return momentum and on institutional investors, the research on the impact of institutional positive-feedback trading on stock return momentum has been relatively sparse. The most related study to my paper is Nofsinger and Sias (1999), which addresses this question by sorting stocks independently on past stock returns and institutional trading. They find that current stock returns increase in both past stock returns and current institutional trading. In addition, regardless of winners or losers, stocks that experience high volume of institutional buys (sells) exhibit higher (lower) returns than the benchmarks with similar past performance. However, as they point out, this relation is not free of the endogeneity problem since they are examining the variables simultaneously. That is, the positive relation between institutional positive-feedback trading and return momentum that they observe can be due to institutional trend-chasing. Moreover, their institutional holding data is on an annual basis, which intensifies the endogeneity problem.

This paper takes a different approach by measuring the positive-feedback trading by institutions at individual stock level. I create a measure, MT (momentum trading), which evaluates the amount of institutional positive-feedback trading on a stock during a certain period of time. On a scale ranging between -5 and 5, a higher MT measure implies that institutions are more likely to buy the stock when its past performance is good and/or sell the stock when its past performance is poor. Moreover, I update the ex-ante MT measure using previous data to avoid the endogeneity problem. In particular, the MT measure of quarter t is calculated using the data of institutional trading and stock returns during the two-year period up to the end of quarter t-1.

Next, I examine the effect of institutional positive-feedback trading on return momentum by exploiting the six-month-formation/six-month-holding momentum strategy across MT levels. Consistent with the hypothesis that positive-feedback trading by institutions contributes to stock return momentum, I find strong empirical evidence that return momentum is increasing in the ex-ante MT measure. For example, when firms are sorted into three MT groups, the monthly momentum profit of the top MT tercile is 0.53% higher than that of the bottom MT tercile. This difference is not only statistically significant, but also economically significant as well, compounded to an annual difference of 8.58%.

Previous research has documented stronger return momentum in stocks of smaller sizes, lower book-to-market ratios (henceforth BE/ME), higher turnovers, lower analyst coverage, higher return volatility and shorter history.[8] My further empirical results suggest that although institutional positive-feedback trading is stronger in small stocks, high BE/ME stocks, high turnover stocks, low coverage stocks, stocks with higher return volatility, and younger stocks, the effect of institutional positive-feedback trading on return momentum is robust after controlling for the effects of these variables.

This paper also has implications for whether institutional trading has price impact. Although numerous studies have documented the positive relationship between institutional trading and stock returns, this phenomenon is not necessarily a result of the price impact of institutional trading. It can also be explained, for example, by institutional information advantage or institutional trend-chasing. For example, Chan and Lakonishok (1995), Nofsinger and Sias (1999), Chakravarty (2001) and Sias, Starks, and Titman (2006) find empirical evidence suggesting that institutional trading is capable of moving stock prices. However, two other studies by Griffin, Harris, and Topaloglu (2003) and Sias (2004) attribute the positive relationship between

[8] See Jegadeesh and Titman (2001), Hong, Lim, and Stein (2000), Daniel and Titman (1999), Lee and Swaminthan (2000), Jiang, Lee, and Zhang (2005), and Zhang (2006) for the relationships between stock return momentum and size, BE/ME, turnover, analyst coverage, return volatility, and firm age.

institutional trading and stock return to either informational advantage or institutional trend-chasing. My paper contributes to this line of research by providing new empirical evidence suggesting that institutional trading moves stock prices when they act as positive-feedback traders.

In addition, this paper presents two pieces of empirical evidence suggesting that institutional positive-feedback trading destabilizes stock prices and hampers market efficiency. First, the price movements caused by institutional positive-feedback trading are not accompanied by the corresponding changes in analyst forecasts of earnings, indicating that institutional positive-feedback trading is not triggered by market underreaction to information on firms' fundamentals; second, I observe much deeper long-term reversals in momentum profits for the stocks that experience more institutional positive-feedback trading, which is evidence that institutional positive-feedback trading drives stock prices further away from the fundamental values of the firms.

To summarize, my dissertation makes important contributions the current finance literature.

First, my dissertation contributes to the literature of market efficiency by showing that institutional trading has important yet complicated impact on stock market efficiency. While institutional trading in general improves price efficiency, some of their particular trading behaviors could hamper price efficiency. In addition, stock market anomalies are significantly intensified with the lack of institutional trading volume.

Second, my dissertation contributes to the literature of institutional investors. The rapid growth of institutional investors has motivated numerous studies on the role of institutions in various stock market phenomena and corporate events. Many studies focus on institution-individual composition of shareholders as measured by institutional ownership. In contrast, trader composition, i.e., which type of investors dominates the *trades* of a stock, has been largely ignored. The first chapter thoroughly studies trader composition, which has been largely ignored by the current literature, and show that trader composition has significant effects on price efficiency and the cross-section of stock returns.

In addition, the second chapter for the first time create a firm-level measure of institutional positive-feedback trading, and reveals that institutional positive-feedback trading contributes to stock return momentum and hampers stock price efficiency.

1 Trader Composition, Price Efficiency, and the Cross-Section of Stock Returns

1.1 Measuring trader composition

This section describes the measurement trader composition. There are three potential methods to evaluate trader composition: split of trading volume associated with institutions and individuals, split of the number of trades, and split of the number of traders. Although all these methods reflect trader composition, in this paper I choose the split of trading volume out of two concerns. First, the number of trades by institutions and individuals is not publicly available. Second, although the approximate number of institutional traders can be inferred from institutional holdings data, the number of individual traders is not publicly available. In addition, even if trader numbers are available, the number of institutions would be so small compared to individuals that any ratio of trader numbers would lack cross-sectional dispersion.

This subsection describes the measurement trader composition. I construct the FIT measure of a stock i in quarter t, i.e., fraction of institutional trading volume in the total trading volume of stock i in quarter t, following the two steps below:

Step1: I first calculate institutional trading volume (henceforth ITV) using the following formula.

$$ITV_{it} = \sum_{j=1}^{N} |IO_{ijt} - IO_{ijt-1}| \tag{1}$$

where ITV_{it} is institutional trading volume (adjusted by the stock's total shares outstanding) of stock i in quarter t. IO_{ijt} is institution j's ownership of stock i for quarter t, calculated as j's share holdings of stock i divided by i's total shares outstanding at the end of quarter t. This formula first approximates the trading volume of each institution by calculating the absolute value of change in ownership, and then aggregates these absolute changes across institutions to obtain the total institutional trading volume.

Step2: I then calculate FIT by adjusting ITV with total turnover of a stock.

$$FIT_{it} = \frac{ITV_{it}}{TO_{it}} \tag{2}$$

where TO_{it} is total turnover of stock i in quarter t.[9] FIT_{it} aims at measuring how actively institutions trade stock i in quarter t relative to individuals.

The construction of the FIT measure is simple and straightforward. However, the issue of round-trip trades could bias downward the estimated institutional trading volume and therefore the FIT measure. For example, if an institution purchases 1% of a stock's shares and then sells it within the same quarter, then the FIT measure will ignore these two trades because they are not included in quarterly institutional ownerships.

Because of the issue of round-trip trades, the trader composition measure actually reflects the fraction of trading volume from relatively long-term institutional investors. If an institution acts as day-trader of a stock and fre-

[9] In each month of quarter t, I divide total trading volume of stock i by its total shares outstanding to obtain monthly turnover. I then sum up the three monthly turnovers in quarter t to obtain TO_{it}, total turnover of stock i in quarter t.

quently makes round-trip trades of the stock within a quarter, then a large portion of the trading of this institution might not be included in the FIT measures. Since different institutions have different trading frequency, the FIT measure could represents trading of certain types of institutions but ignore other institution types. For example, Carhart (1997) document that mutual funds, which are relatively active institutional traders, have average turnover of 77.3% a year, which is equal to a holding period of 15.5 months or over five quarters, which is well above the one-quarter interval of our trading volume calculation. Therefore, the FIT measure could capture the majority of the mutual fund trading and less active institutions such as pension funds, banks, or investment advisors. However, the FIT measure could miss a significant amount of hedge fund trading or the trading of institutional day-traders, since these institutions could trade at much higher frequency than other institution types and incur large volumes from round-trip trades. Therefore the effects of the FIT measure actually reflects the effect of the trading volume from the relatively long-term institutional traders. As a result, the tests with the FIT measure indicates the effect of the trading from relative long-term institutional traders on price efficiency.

In addition, the issue of double counting could bias upward the estimated institutional trading volume and therefore the FIT measure, since the FIT measure double counts the trades between two institutions. As a result, FIT is ranging between 0 and 2 rather than between 0 and 1. For example, suppose an extreme case where a stock i is traded only once, which is institution A selling 1% of stock i's total shares to institution B. Then the absolute change in ownership will be 1% for both A and B, leading to an ITV of 2%. Since turnover is 1%, the FIT measure in this case will be 2, calculated as 2% divided by 1%. Double counting occurs because the data does not allow us to disentangle trades between two institutions and trades between an institution and an individual.

In order to separately examine the effects of institutional buys and sells, I further decompose the FIT measure into FIB, fraction of institutional buy volume in the total trading volume, and FIS, fraction of institutional sell volume in the total trading volume. In particular, if an institutions increase (decrease) its ownership of a stock during a quarter, then I treat this change as a buy (sell).

Some may argue that any effect of the FIT measure might be liquidity effect because turnover is the denominator of FIT, and turnover itself is a liquidity measure. To address this issue, I directly control for turnover by creating a residual trader composition measure which are residuals from the regression of the FIT measure on turnover. The residual FIT measure is therefore orthogonal to turnover and able to eliminate the liquidity effect, if any, introduced by turnover. I then repeat the tests with this turnover-adjusted FIT measure and the results are very similar to the original FIT measure. I also create an alternative turnover-adjusted FIT measure with benchmark process. In particular, I subtract from the FIT of a firm the average FIT measure of the turnover quintile the firm falls in. The results are also very similar with this alternative turnover-adjusted FIT measure. Therefore these results with the turnover-adjusted measures show that the FIT effect is not caused by its correlation with liquidity.

1.2 Data and Sample Selection

I obtain quarterly institutional share holdings from the CDA/Spectrum Institutional (13f) database, which contains the filings by institutions under Section 13f of the Security and Exchange Act of 1934. Stock data such as returns, price, shares outstanding and trading volume are obtained from CRSP, while annual accounting data and quarterly earnings-announcement data of the firms are obtained from COMPUSTAT. I obtain analyst coverage from IBES and the benchmark portfolio returns of MKT, HML, SMB and UMD from Kenneth French's data library.[10] My sample period starts from 1980 through 2005 because of the availability of 13f data.

My sample is the overlap of 13f and CRSP data. In addition, if in a quarter an institution does not report holding of a stock in 13f but the stock has a record in CRSP, I do not drop this stock but instead set the holding of this institution to zero. When calculating the change in institutional ownership of a quarter, I include only the institutions that report holdings of at least one stock in 13f at both the beginning and the end of the quarter. I apply this filter because of the entry-and-exit issue. Since only institutions with total holdings over 100 million dollars are required to file 13f, some institutions might report intermittently because of the fluctuation of total holdings. Therefore I introduce this filter to control for the entries and exits of institutions in the 13f database.

My sample is restricted to NYSE/AMEX firms because trading volumes of Nasdaq stocks are inflated relative to those of NYSE/AMEX stocks by different trading systems. In addition, I keep only the firms with CRSP histories of at least six months. In order to control for the microstructure

[10]See $http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html$.

effects, I drop the stocks priced below $5 and stocks with market capitalizations below NYSE 10% breakpoints, as did Jegadeesh and Titman (2001). I also drop the firms with negative BE/ME. The following subsections will introduce additional restrictions for some of the tests in this chapter.

1.3 Determinants of trader composition

1.3.1 Summary Statistics

My final sample contains 236,908 firm-quarter observations with the available trader composition measures from the third quarter of 1980 to the last quarter of 2005, with average 2,323 firms in each cross-section. Since the upper limit is 2 for FIT and 1 for FIB and FIS, I winsorize FIT at 2 and FIB and FIS at 1 in order to avoid data errors. Table 1 presents the sample distributions of FIT, FIB and FIS. The mean FIT is 54% equal weighted (62% value weighted), indicating that institutions account for over half of the trading volume in the sample period. In addition, FIT, FIB and FIS are rather dispersed cross sectionally, which shows that different stocks have very different trader composition.

Table 1 also summarizes institutional ownership and firm characteristics including market capitalization, BE/ME, beta, turnover, past return, residual analyst coverage, stock price, idiosyncratic volatility, dividend yield and stock illiquidity. I examine Beta, firm size, BE/ME and past returns because they affect stock returns. I further include analyst coverage, stock price, stock illiquidity, idiosyncratic volatility (firm specific risk), and dividend yield because previous studies observe that they are related to institutional ownership.[11] Last, I construct a dummy variable for S&P500 composite index because trader composition might differ for index firms.

Beta (obtained from CRSP) is estimated annually with daily returns of a stock in the previous calendar year; firm size is the natural log of a firm's market capitalization; BM/ME is the summation of a firm's book equity and deferred tax divided by the firm's market equity; past return is the cumulative return of a firm during the past six months. The residual analyst coverage is calculated following Griffin and Lemmon (2002) by adjusting a firm's analyst coverage with average coverage of the firm's NYSE size quartile. Turnover is quarterly turnover of a stock by summing up three monthly turnovers during the quarter, where monthly turnover is monthly trading volume divided by shares outstanding. Dividend yield is a firm's dividend payment per share divided by its share price. I apply the accounting variables at fiscal year end of t to the one-year period starting from the July of year $t+1$. I winsorize turnover, BE/ME and ITV at 99% cutoff points to control for the outliers and data errors.

I estimate idiosyncratic volatility every month with a five-year rolling window procedure. Specifically, for each month t, I run a time-series regression of a stock's monthly excess returns on the monthly market excess returns (MKT), SMB and HML for the five-year period up to t. Next, I calculate idiosyncratic volatility of this firm as the standard deviation of residuals.[12] I then apply the obtained idiosyncratic volatility to month $t+1$. I only include the firms with more than 24 monthly returns in the five-year estimation

[11]See Dahlquist and Robertsson (2001) Bennett, Sias, and Starks (2003) and Grinstein and Michaely (2005) for the relationship between institutional ownership, idiosyncratic volatility and dividend yield.

[12]I adjust for three degrees of freedom when calculate the standard deviation so that the estimate is unbiased. My results are not changed when I instead use CAPM or 4-Factor Model to estimate idiosyncratic volatility.

windows to avoid estimation errors.

The illiquidity measure is estimated following Amihud (2002) with the formula:

$$Illiq = \frac{1}{T}\sum_{t=1}^{T}\sqrt{\frac{|r_t|}{vol_t}} \tag{3}$$

where r_t is the stock return on day t and vol_t is the reported dollar volume on day t. The average is computed over all days in the samples for which the ratio is defined, i.e. days with nonzero volume. This measure reflect the return impact of a cumulative signed order flow. I estimated the illiquidity measure annually and applied the estimated measure to the next calendar year. Following Amihud (2002), I drop the firms with less than 200 valid observations of volumes in the estimation period.[13]

1.3.2 Determinants of Trader Composition

Many previous studies investigate the relationships between institutional ownership and firm characteristics such as size, BE/ME, past returns, stock liquidity, etc.[14] In contrast, the determinants of trader composition have never been studied. This subsection is intended to address this research question.

I start with Table 19 which presents firm characteristics across FIT groups. Specifically, in each quarter I sort stocks into quintiles of FIT and report the

[13]This is a transformed Amihud (2002) measure suggested by Hasbrouck (2006). My results are not changed when I estimate the original Amihud (2002) illiquidity measure without taking the square root of the fractions in equation (7).

[14]An incomplete list includes Del Guercio (1996), Falkenstein (1996), Gompers and Metrick (2001), Dahlquist and Robertsson (2001), Badrinath and Wahal (2002), Bennett, Sias, and Starks (2003), Hartzell and Starks (2003), Grinstein and Michaely (2005), and Han and Wang (2005).

time-series averages of the cross-sectional means of the characteristics for each quintile. FIB and FIS are in the same quarter and the other variables are measured at the beginning of the quarter. Table 19 shows that the fraction of institutional trading volume is positively related to FIS, FIB, institutional ownership, firm size, analyst coverage, stock price and the S&P 500 dummy, and negatively related to dividend yield and illiquidity. The relationships between FIT and turnover, beta and analyst coverage are mixed, where both the top and bottom FIT quintiles have lower turnovers, betas and coverages than the medium quintiles. In addition, FIT does not have significant relationships with BE/ME ratios, past returns and idiosyncratic volatilities.

Since Table 19 does not examine different firm characteristics simultaneously, I further run the following multivariate Fama-Macbeth regression.

$$FIT_{it} = \beta_1 + \sum_{m=2}^{K} \beta_m X_{mit-1} \tag{4}$$

Where FIT_{it} is FIT of stock i of quarter t; X's include institutional ownership and firm characteristics. All the independent variables are measured at the beginning of quarter t. In order to control for the autocorrelation of FIT, I also include the one quarter lag FIT into the independent variables. To facilitate the evaluation of economic significance, I follow Chan, Jegadeesh, and Lakonishok (1996) to transform all the independent variables except the S&P500 dummy into standardized ranks between 0 and 1. Particularly, in each cross-section, I rank stocks according their levels of a variable, and then divided these ranks by the total number of stocks in this cross-section. In this way, this variable is evenly spread between 0 and 1, where 0 represents the minimum and 1 represents the maximum.

Before running the regressions, I first report in Table 3 time-series averages of the cross-sectional correlations between the variables. The correlation between FIT and lag FIT is as high as 0.68, which is evidence of strong persistence in trader composition. Interestingly, the correlation between FIT and lag institutional ownership is also as high as 0.48, indicating a strong positive relationship between traders composition and shareholder composition. In the meantime, FIT is positively correlated with firm size, BE/ME, beta, stock price, S&P500 dummy, and negatively correlated with past return, idiosyncratic volatility, dividend yield and the illiquidity measure. Since the illiquidity measure and firm size are almost perfectly correlated (correlation -0.86), to avoid the multi-collinearity problem, for the rest of the tests in this section I use a residual illiquidity measure obtained from the cross-sectional regression of illiquidity on firm size.

Table 4 reports the regression results. I start with Model (1) that regresses FIT on its lag because of the strong autocorrelation of FIT shown in Table 3. The coefficient of lag FIT is 0.93, significant at the 0.01 level. The Adjusted R-square of 0.4183 indicates that lag FIT alone explains a substantial amount of the variation in FIT. According to the coefficient of 0.93, the difference in FIT between the top and bottom lag FIT quintiles is as high as 74.4%.[15]

Model (2) include firm characteristics other than lag FIT, which produces three major empirical results . First, the coefficient of lag FIT is only slightly reduced from 0.93 in Model (1) to 0.89 in Model (2), which shows that historical FIT has strong explanatory power even after controlling for

[15]The 74.4% difference is calculated as follows. Recall that lag FIT is standardized between 0 and 1. Therefore the mean lag FIT is 0.90 for the top lag FIT quintile and 0.10 for the bottom lag FIT quintile. The difference in lag FIT is therefore 0.80. As a result, the difference in FIT between the top and bottom lag FIT quintiles is 0.80 times the coefficient 0.93, which leads to 74.4%.

firm characteristics and institutional ownership. Second, the coefficient of institutional ownership is as high as 0.23 and significant at the 0.01 level, suggesting that trader composition is closely related to shareholder composition. Last, trader composition is also related to firm characteristics. In particular, FIT is positively related to firm size, BE/ME, and illiquidity, and negatively related to Beta, past returns, price, S&P500 dummy, analyst coverage, idiosyncratic volatility, and dividend yield. Model (3) is similar to Model (2) but excluding the lag FIT term, in which the coefficients of all firm statistics remain the same sign and statistical significance. However, the magnitudes of the coefficients are much larger than in Model (2), showing that the lag FIT term subsumes much of the effects of firm characteristics.

Model (2) shows that five firm characteristics including institutional ownership, illiquidity, idiosyncratic return volatility, S&P 500 dummy and residual analyst coverage have the biggest coefficients next to the lag FIT measure, indicating that these firm characteristics also have significant effects on trader composition as follows.

First, FIT increases in institutional ownership. This could be caused by two facts. First, institutions know the stocks in their portfolios better, so they tend to trade these stocks more frequently. Second, it could be a mechanical relationship because institutions can only sell when they hold a stock. Therefore ownership is positively related to institutional sell volume and then total institutional trading volume. Model (5) and (7) suggest that both explanations are valid, where both coefficients of institutional ownership are significantly positive but the coefficient in the FIS regression is much bigger in magnitude.

Second, FIT increases in illquidity. That is, FIT is *lower* for liquid stocks controlling for other characteristics. This interesting result is a sharp contrast to the fact that institutions tend to hold liquid stocks.[16] This result indicates that while institutions hold more liquid stocks relative to individuals, they tend to trade illiquid stocks more than individuals.

Third, FIT decreases in analyst coverage and S&P500 dummy controlling for other characteristics. This result is interesting because institutions tend to hold high analyst coverage firms and index firms.[17] This result could be related to two phenomena. First, on the institutions side, although index funds hold a large number of index shares, they do not trade frequently other than rebalancing. Second, on the individuals side, Odean (1999) finds that for individual traders, the difficulty in searching for securities could lead to a tendency to let their attention be directed by outside sources. As a result, individuals tend to trade the stocks that attract their attention. Therefore, individuals tend to trade index firms or firms with higher coverage because these firms are associated with more events and greater media exposure, which can lead to lower fractions of institutional trading volume.

Model (1), (2) and (3) reveal that trader composition is relatively persistent over time. This result is further confirmed by the FIB regression in Model (5) as well as FIS regression in Model (7), where the coefficients of lag FIB and lag FIS are both of large magnitudes and statistically significant. Therefore, investigating the persistence in trader composition is necessary if we want to study trader composition is determined. I examine several potential explanations of the persistence in trader composition.

First, we can rule out the possibility of persistence being a mechanical

[16]Previous studies, for example, Bennett, Sias, and Starks (2003), Del Guercio (1996), and Falkenstein (1996) show that institutions tend to hold liquid stocks.

[17]See, for example, Gompers and Metrick (2001), Del Guercio (1996) for the relationships between institutional ownership, coverage and index composition.

relationship introduced by construction. Although institutional ownership is rather persistent due to its nature of a cumulative measure, the FIT measure is not necessarily to be persistent. As discussed in Section 2.1, FIT is in the similar spirit to an incremental measure.

Second, it is possible that the persistence found in the regressions is caused by some FIT outliers. To address this concern, I sort stocks into deciles of the one quarter lag FIT and report the average portfolio FIT in the current quarter. Table 5 Panel A shows that FIT measures are monotonically increasing in the lag FIT levels with a big differences between the two extreme lag FIT portfolios. For example, FIT of the top historical FIT decile is 99.39%, much higher than 6.46%, FIT of the bottom historical FIT decile. The difference is 92.92%, almost twice of the mean FIT. Panel B and Panel C also present monotonic relationships for FIB and FIS. These results are inconsistent with the outliers explanation.

Third, window dressing could cause the persistence in trader composition. Specifically, by 'window dressing' institutions dump past losers at quarter ends, especially at year ends, and buy them back in the next quarter, which could cause positive correlation between institutional trading volumes across quarters.[18] Since the effect of window dressing is limited to the two adjacent quarters, I repeat the FIT regressions in Table 4 but replace the first lag of FIT with the second lag. The results are not reported for brevity, but the regression results show that persistence in trader composition is robust with the second lag of FIT, which is inconsistent with the explanation of window dressing.

Fourth, institutions are known to split their trades over a time period of

[18]See, for example, Lakonishok, Shleifer, and Vishny (1992), Sias and Starks (1997), and Ng and Wang (2004) for window dressing.

up to seven days to reduce trading costs.[19] If institutions happen to split their trades around the turn of a quarter, then institutional trading volumes of the two adjacent quarters could be positively correlated. However, this explanation is inconsistent with the aforementioned result that the persistence is robust with the second lag of FIT, because the effect of split of trades is also limited to two adjacent quarters.

Last, I examine the explanation based on information asymmetry and find supportive evidence. In particular, Froot, Scharfstein, and Stein (1992) and Hirshleifer, Subrahmanyam, and Titman (1994) reveal that in the presence of information asymmetry, if some investors learn information earlier than their peers, then even rational investors will focus on some securities but ignore others with similar characteristics. Therefore, for stocks with information asymmetry, rational investors, in our case institutional investors, will concentrate their trading in some stocks but ignore others in a period of time, therefore lead to persistence in trader composition during in this time period.

I conduct a test on information asymmetry hypothesis by examining the persistence across firms with different analyst coverage.[20] According to Froot, Scharfstein, and Stein (1992) and Hirshleifer, Subrahmanyam, and Titman (1994), we would expect the persistence to be stronger less covered stocks because they are associated with more information asymmetry. Table 4 Model (4), (6) and (8) present FIT, FIB and FIS regressions that include the interactions of residual analyst coverage with lag trader composition measures.

[19] Chan and Lakonishok (1997) shows that institutions split their trades over a period as long as seven days. They find little evidence of trade split beyond seven days.

[20] For this test I employ a residual analyst coverage measure constructed following Griffin and Lemmon (2002) by adjusting a firm's analyst coverage with the average analyst coverage of the NYSE size quartile of the firm.

Consistent with the costly information hypothesis, all the interaction coefficients are significantly negative, indicating stronger persistence low analyst coverage stocks.

To summarize, this section shows that that although institutional ownership as well as firm characteristics affect trader composition, the most important determinant of a firm's trader composition is its historical trader composition.

1.4 Trader Composition and the Cross-Section of Stock Returns

1.4.1 Direct Relationship Between Trader Composition and Stocks Returns

This subsection studies the direct effect of trader composition on stock returns by testing two competing hypotheses. On one hand, according to the conlcusion by DeLong, Shleifer, Summers, and Waldmann (1990a), we would expect low FIT stocks to earn higher returns than high FIT stocks. Specifically, the theoretical study of DeLong, Shleifer, Summers, and Waldmann (1990a) show that the stocks intensively traded by noise traders earn higher returns, a phenomenon they called 'noise trader risk'.

On the other hand, low FIT stocks could earn lower returns because of the following two aspects of mispricing. First, according to our hypothesis, mispricing is more intensive in the stocks with lower fractions of institutional trading volume. Second, although mispricing could take the form of overpricing or underpricing, overpricing could be the major form of mispricing. To arbitrage way overpricing, an investor often needs to sell short a stock which could be costly or constrained.[21] For example, Almazan, Brown, Carlson, and Chapman (2004) report that over 80% of mutual fund managers are not allowed to short sell. Consistent with overpricing being the major form of mispricing, previous studies find that abnormal returns of the trading strategies employing the anomalies such as price momentum, IPO underperformance, and the value premium come mainly from the short side, indicating that overpricing is the source of these anomalies. Given that overpricing is the predominant form of mispricing, if mispricing is more intensive in low FIT stocks, then low FIT stocks are overpriced and therefore will earn lower returns in the next period.

To test the two competing hypotheses, I sort stocks into FIT deciles and examine monthly returns in the next quarter. I also report Jensen alphas and Carhart (1997)'s four-factor alphas. In addition to the regression approach, I also calculate DGTW returns obtained from the benchmark-portfolio procedure for the FIT deciles.[22] In order to control for the time-series correlation of stock returns, I calculate all the t-statistics using Newey-West robust standard errors. Without otherwise specified, all the t-statistics in the sub-portfolio analysis are calculated with Newey-West robust standard errors. To separate the effect of trader composition from institutional ownership, I repeat the sub-portfolio analysis with the residual FIT measure. To construct the residual FIT measure (ResFIT), in each quarter I run an OLS regression of the FIT measure on institutional ownership at the beginning of the quarter and then take residuals from the regressions.

Panel A of Table 6 show that, consistent with the overpricing hypothe-

[21]See, for example, Geczy, Musto, and Reed (2002), Chen, Hong, and Stein (2002), Nagel (2005) and Asquith, Pathak, and Ritter (2005) for short sale costs and short sale constraints.

[22]I thank Russ Wermers for providing the DGTW benchmark portfolio returns.

sis, low FIT stocks earn lower returns. In particular, the bottom FIT decile underperform the top FIT decile by 0.29% to 0.57% per month with different return adjustments, and the differences are statistically significant at the standard levels. In addition, Panel B reports the results with the residual FIT measure. The return differences are 0.20% to 0.42% per month according to various return adjustments and significant at the standard levels, indicating that the result in Panel A is robust after controlling for institutional ownership.

One interesting question is how the effect of trader composition interact with stock illiquidity. Institutions generally trade in large size and individuals trade in relatively small size.[23] Therefore, institutional trades could more effectively move the prices of illiquid stocks. As a result, even though a illiquid stock has low fraction of institutional volume and is mispriced, the intensity of mispricing is alleviated because for this stock, institutional trades can move stock prices and improve price efficiency more effectively. Therefore, for illiquid low FIT stocks, we expect to see less inferior return in the subsequent period than liquid low FIT stocks. Consequently, we expect to see the return difference between high FIT and low FIT stocks bigger in liquid stocks.

To test this hypothesis, I report in Table 7 the monthly stock returns of the portfolios two dimensionally sorted on lag FIT measure and Amihud (2002)'s stock illiquidity measure. Consistent with the our hypothesis, the return difference between low FIT and high FIT stocks is much bigger in liquid stocks. For example, the returns between the top and bottom FIT

[23]For example, Griffin, Harris, and Topaloglu (2003) finds that institutional trades account for 86% of large trades but only 22% of small trades for Nasdaq100 stocks. In their paper, trade sizes of less than 500 shares are designated as small trades and share increments of greater than 10,000 shares are classified as large trades.

quintile is 0.69% for the most liquid group but only 0.28% for the most illiquid group. In addition, this table shows that the difference comes mainly from the low FIT groups. The returns of the low FIT quintile is 0.67% for the most liquid group, much lower than that of the low FIT quintile in most liquid group, 1.17%. This provides further supporting evidence of the previous hypothesis that low FIT stocks are overpriced and therefore earn lower subsequent returns.

1.4.2 Trader Composition and Stock Return Momentum

This subsection, as well as the next two subsections, investigates the relationships between trader composition and stock market anomalies. If mispricing is more intensive in stocks with lower fractions of institutional volumes, then we would expect stock market anomalies involving mispricing to be more pronounced in low FIT stocks.

In this subsection I focus on the effect of trader composition on return momentum. I first examine the profits of 6-month/6-month momentum strategy across FIT groups. In particular, at the beginning of each month, an independent sort is used to rank stocks into three groups of the FIT measure of the previous quarter, and ten groups of their past six-month returns. Each of these 30 two-dimensional portfolios are then held for six months.[24] In order to control for the microstructure effects, I skip one month between portfolio formation and return measurement as in Jegadeesh and Titman (1993). Table 8 Panel A reports the results. Although the momentum profits are significant across all FIT groups, the average monthly momentum profit in the bottom FIT group is 1.48%, much higher than 0.95%, the momentum profits

[24]The momentum strategy is the same as in Jegadeesh and Titman (1993).

in the top group. The difference in momentum profits between the top and the bottom tercile is 0.53%, both economically and statistically significant (t-stat 3.12). Panel B repeats the test but with the residual FIT measure which controls for institutional ownership. The result is close to Panel A: momentum profit of the bottom ResFIT tercile is 0.47% (t-stat 2.93) higher than that of the top ResFIT tercile.

I adopt quarterly multivariate Fama-Macbeth regressions to further control for other factors affecting momentum such as size, BE/ME, analyst coverage and turnover.[25] The regressions also control for institutional ownership because of its strong positive relationship with the FIT measure.

Each quarter I run a cross-sectional regression of quarterly cumulative stock returns on the control variables including the interactions of past six-month returns with FIT, FIB, and FIS, and then report the time series means and t-statistics of the coefficients. I also include the interactions of past six-month returns with institutional ownership, firm size, BE/ME, turnover, and residual analyst coverage. The regressions also include firm characteristics such as Beta, size and BE/ME to control for their effects on stock returns. In order to facilitate the evaluation of economic significance, I follow Chan, Jegadeesh, and Lakonishok (1996) to transform all the independent variables except the S&P500 dummy into standardized ranks between 0 and 1, where 0 represents the minimum and 1 represents the maximum. I also skip a month before return measurement in order to control for the microstructure effects.

Table 9 reports the regression results, where Model (1) regresses quarterly returns on past six-month returns, interaction of past return with lag

[25] See Jegadeesh and Titman (2001), Hong, Lim, and Stein (2000), Daniel and Titman (1999) and Lee and Swaminthan (2000) for the relationships between return momentum and firm size, analyst coverage, BE/ME and turnover.

FIT, and firm characteristics such as Beta, firm size and BE/ME.[26] Consistent with the portfolio analysis in Table 8 Panel A, the coefficient of the FIT interaction is -4.21 (t-stat -4.08), indicating that return momentum is decreasing in lag FIT. This effect is also economically significant, showing that after controlling for Beta, size and BE/ME, return momentum is about 2.50% per quarter stronger in the bottom FIT tercile than in the top FIT tercile.[27] Model (2) examines interaction between past return and institutional ownership, which shows that return momentum is also negatively related to institutional ownership. However, coefficient of IO interaction is only about 60% of the the coefficient of FIT interaction, indicating that effect of institutional ownership on return momentum is much weaker than the effect of FIT. Next, I put interaction terms of past returns with both FIT and institutional ownership in Model (3), where the interaction of lag FIT remains almost the same but the interaction of lag institutional ownership becomes insignificant.

Model (4) further controls for the effect of size, BE/ME, turnover and residual analyst coverage on return momentum by including their interaction terms with past returns. There are two apparent results. First, consistent with previous studies, the interaction terms of size, BE/ME, turnover and residual analyst coverage show that return momentum is stronger in small stocks, growth stocks, high turnover stocks and low coverage stocks.[28] Second, in Model (4) the coefficient of the FIT interaction is reduced to -2.78 from -4.20 in Model (1). This result shows that on one hand, part of the

[26]Constants are not reported for brevity.

[27]Return momentum is measured by the difference in quarterly return between the top and bottom past return deciles, and the 2.50% difference is calculated as 0.66(difference in standardized lag FIT between top and bottom lag FIT terciles) times 0.9(difference in standardized past return rank between top and bottom lag past return deciles) times -4.21, the coefficient of the interaction term.

[28]See Jegadeesh and Titman (2001), Hong, Lim, and Stein (2000), Daniel and Titman (1999) and Lee and Swaminthan (2000) for the relationships between return momentum and firm size, BE/ME, analyst coverage and trading volume.

trader composition effect on return momentum is subsumed by the control variables; on the other, the remaining effect of trader composition is still considerably large. For example, in Model (4) the coefficient of FIT interaction, -2.78, suggests that after controlling for other factors in the regression, return momentum is about 1.65% per quarter stronger in the bottom FIT tercile than in the top FIT tercile.[29]

In order to investigate the contributions of FIT's components to its effect on return momentum, I include the interactions of past returns with FIB and FIS in Model (5) to (7). Specifically, Model (5) examines the interactions of past returns with FIB and FIS; Model (6) further controls for institutional ownership, and Model (7) controls for the effects of other characteristics on return momentum. The coefficients of FIS interactions are significant but the coefficients of FIB interactions are not. For example, in the most comprehensive model of (7), the FIS interaction is -2.05 (t-stat -2.26) but the FIB interaction is only -0.94 (t-stat -1.01). These results shows that the FIS has much stronger effect on momentum than FIB.

To summarize, this subsection presents strong evidence that after controlling for firm characteristics and the effects of the known factors on return momentum, stocks with lower fractions of institutional trading volumes exhibit significantly stronger return momentum. Further evidence shows fraction of institutional sell volume has much stronger effect on momentum than does fraction of institutional buy volume.

[29]Return momentum is measured by the difference in quarterly returns between the top and bottom past return deciles, and the 1.65% difference is calculated as 0.66(difference in standardized lag FIT between top and bottom lag FIT terciles) times 0.9 (difference in standardized past returns between top and bottom past return deciles) times -2.78, the coefficient of the interaction term.

1.4.3 Trader Composition and Post Earnings-Announcement Drift

This subsection studies the relationship between trader composition and post earnings-announcement drift. For this purpose I employ a trading strategy based on earnings-announcement shock proposed by Frazzini (2005). In particular, at the beginning of each month, an independent sort is used to rank stocks into three groups of FIT of previous quarter and ten groups of their most recent quarterly earnings-announcement shock (will be defined soon). Each of the 30 two-dimensional portfolios are then held for six months.[30] There is a one-month interval between portfolio formation and return measurement in order to control for microstructure effect. This rolling PEAD strategy is similar to Jegadeesh and Titman (1993)'s momentum strategy except that stocks are sorted on earnings-announcement shocks rather than past returns.

Quarterly earnings-announcement shocks are measured using the market model abnormal returns from two days prior to the quarterly announcement date to one day after the announcement date. The estimation window is the 255 trading days up to the $46th$ trading day before the earnings announcement. I drop the firms with less than 128 daily returns in the estimation period to avoid estimation errors. I obtain quarterly earnings-announcement dates from quarterly CompuStat database and use CRSP value weighted index as market return. I use stock market reaction rather than earnings surprise to measure earnings-announcement shock because this method avoids the bias associated with analyst forecast.

Panel A of Table 10 reports performance of PEAD strategy across FIT

[30] In order to avoid a too long time interval between earnings announcement shock and return measurement, I drop the firms without an earnings announcement record in the three-month period prior to portfolio formation.

groups, which shows that that PEAD is much stronger in low FIT stocks than in high FIT stocks. Specifically, the average monthly PEAD profit in the bottom FIT tercile is 0.82%, much higher than that of the top FIT tercile, 0.32%. The difference in PEAD profit between the two extreme FIT terciles is 0.50%, both economically and statistically significant (t-stat 4.21). I then repeat the test with the residual FIT measure and report the results in Panel B. The PEAD profit is 0.26% (t-stat 2.45) higher in the bottom ResFIT tercile than in the top ResFIT tercile.

I further examine the effects of trader composition on PEAD in a framework of quarterly multivariate Fama-Macbeth regression. Specifically, in each quarter I run a cross-sectional regression of quarterly cumulative stock returns on a set of independent variables including the interactions of earnings-announcement shock with FIT, FIB and FIS. Then the time-series means and t-statistics of the coefficients are reported. I also include the interaction of earnings-announcement shock with institutional ownership and firm size because previous studies have found that PEAD is stronger in low ownership stocks and small stocks.[31] Last, I control for Beta, size, BE/ME and past returns in regressions. Like in the previous subsection, I follow Chan, Jegadeesh, and Lakonishok (1996) to transform all the independent variables into standardized ranks between 0 and 1 to facilitate the evaluation of economic significance. I also put a one-month interval before the return measurement to control for the microstructure effects.

Table 11 reports the results of regressions. Model (1) regresses quarterly stock returns on the past earnings-announcement shocks, its interaction with lag FIT, and firm characteristics such as Beta, firm size, BE/ME and past

[31] See Bartov, Radhakrishnan, and Krinsky (2000) for the relationship between post earnings-announcement drift, firm size and institutional ownership.

returns. Consistent with the sub-portfolio analysis in Table 10 Panel A, the coefficient of this interaction is -2.63 (t-stat -3.80), confirming that PEAD is stronger in low FIT stocks. This effect is also economically significant, indicating that PEAD is about 1.56% per quarter stronger in the bottom FIT tercile than in the top FIT tercile.[32] Model (2) examines the interaction of earnings-announcement shock with institutional ownership, which shows that PEAD is decreasing institutional ownership, although this effect is slightly weaker than FIT effect.

I then put the interaction terms of earnings-announcement shock with both FIT and institutional ownership into Model (3). There are two apparent results: first, consistent with Bartov, Radhakrishnan, and Krinsky (2000), the interaction of ownership is -1.66% (t-stat -2.17), indicating the effect of institutional ownership is significant; second, although the interaction of lag FIT is reduced to -1.80% (t-stat -2.43), the FIT effect on PEAD is still economically and statistically significant. Specifically, this number indicates that PEAD is about 1.07% per quarter stronger in the bottom FIT tercile than in the top FIT tercile.[33]

Model (4) further includes the interaction between firm size and earnings-announcement shock. We can see in Model (4) that the effect of firm size on PEAD is rather strong, with the size interaction as big as -3.07 (t-stat 4.17).

[32]PEAD is measured by the difference in quarterly return between the top and bottom deciles of earnings-announcement shock deciles, and the difference of 1.56% is calculated as 0.66(difference in standardized lag FIT between top and bottom lag FIT deciles) times 0.9 (difference in standardized earnings-announcement shocks between top and bottom deciles of earnings announcement shocks) times -2.63, the coefficient of the interaction term.

[33]PEAD is measured by the difference in quarterly return between the top and bottom earnings-announcement shock deciles, and the difference of 1.07% is calculated as 0.33(difference in standardized lag FIT between top and bottom lag FIT terciles) times 0.9 (difference in standardized earnings-announcement shocks between top and bottom deciles of earnings announcement shocks) times -1.80, the coefficient of the interaction term.

In the meantime, the coefficient of FIT interaction is only marginally reduced to -1.54 from -1.80 in Model (3), remaining significant at the standard level. In contrast, the interaction of institutional ownership is substantially reduced to -0.50 from -1.66 in Model (4), becoming insignificant at the standard level. These results show that after controlling for the effect of firm size on PEAD, the effect of trader composition on PEAD persists.

Model (5) to (7) further examine the effects of FIB and FIS on PEAD by including their interactions with earnings announcement shocks. Specifically, Model (5) examines the interactions of earnings announcement shocks with FIB and FIS; Model (6) further controls for institutional ownership, and Model (7) controls for the effects firm size on PEAD. The results shows that the FIS interactions are significant but the FIB interactions are insignificant. For example, in the full model of (7), the FIS interaction is -1.45 (t-stat -1.95) but the FIB interaction is only -0.41 (t-stat -0.46). these results reveal that the relationship between FIT and momentum comes mainly from the effect of FIS.

One interesting question is the relationship between trader composition and earnings-announcement returns. Information revealing is one of the two channels through which trading composition affects price efficiency. If institutions act as rational traders, then their trades could reveal information and improve information transparency. As a result, we would expect that for stocks with higher fraction of institutional trading volume, there is less 'surprise' in stock returns around an information event such as earnings announcement. Therefore a testable hypothesis is that high FIT stocks will have less extreme earnings-announcement returns than low FIT stocks.

To test this hypothesis, I calculate the four-day market model adjusted abnormal returns around quarterly earnings announcements for the sample firms. Then for each month, I sort firms with quarterly earnings-announcements in that month into deciles of one-quarter lag FIT. I then pool the earnings-announcement returns for each FIT decile, fit these returns into normal distribution, and plot the distributions across the FIT deciles. Figure 1 plots the distributions of the earnings-announcement returns for the bottom FIT decile, the 4th FIT decile, the 7th FIT decile, and the top FIT decile. Figure 1 shows a very clear monotonic pattern that as FIT decreases, there are more extreme earnings-announcement returns as indicated by fatter tails of the distributions. This result is consistent with my hypothesis that higher fraction of institutional trading volume leads to more information transparency and therefore more price efficiency.

To summarize, this subsection presents strong empirical evidence that after controlling for price factors and the effect of institutional ownership and firm size on PEAD, the stocks with lower fractions of institutional volumes exhibit significantly larger PEAD. Further evidence show that fraction of institutional sell volume has stronger effect on PEAD than does fraction of institutional buy volume.

1.4.4 Trader Composition and The Value Premium

This subsection studies the relationship between trader composition and the value premium. I start with sub-portfolio analysis where at the beginning of each month, an independent sort is used to rank stocks into three groups of one quarter lag FIT and ten groups of their book-to-market ratios. I calculate monthly returns of the 30 two dimensional portfolios, and then report the time series means and t-statistics of the monthly portfolio returns.

Panel A of Table 12 reports the value premiums across the FIT groups, which reveals that the value premium is much bigger in the stocks with lower FIT. For example, the monthly value premium in the bottom FIT tercile is 0.90%, much higher than 0.27%, the value premium in the top tercile. The difference in the value premium between the top and the bottom terciles is 0.63%, both economically and statistically significant (t-stat 3.09). Panel B shows that the difference in the value premium is 0.41 (t-stat 2.07) higher in the bottom ResFIT tercile than the top ResFIT tercile. Panel C and D further examine the value premiums across FIB and FIS groups. The difference in the value premiums between the top and bottom terciles is 0.53% (t-stat 2.70) for FIB and 0.65% (t-stat 3.23) for FIS. To summarize, this table presents strong evidence that the value premium is bigger in stocks with lower fraction of institutional trading volume.

Similar to the previous two subsections, I further investigate the results obtained from sub-portfolio analysis in a framework of monthly Fama-Macbeth regressions. Specifically, each month I run a cross-sectional regression of monthly stock returns on a set of independent variables including the interactions of BE/ME with FIT, FIB and FIS. I then report the time-series means and t-statistics of the coefficients. I also interact BE/ME with institutional ownership and firm size because previous studies have found that the value premium is stronger in low ownership stocks and small stocks.[34] Last, I add firm characteristics such as beta, firm size, and past returns to control for their effects on stock returns. In order to facilitate the evaluation of economic significance, I follow Chan, Jegadeesh, and Lakonishok (1996) to transform all the independent variables into standardized ranks between

[34]See Fama and French (1992) and Nagel (2005) for the relationship between the value premium and firm size and institutional ownership.

0 and 1.

Table 13 reports the regression results. Model (1) regresses returns on BE/ME, its interaction with lag FIT, and price factors such as beta, firm size, and momentum. The coefficient of the FIT interaction is -0.79 (t-stat -3.02), confirming that the value premium is bigger in low FIT stocks. This effect is also economically significant, indicating that after controlling for price factors, the value premium is about 0.47% per month stronger in the bottom FIT tercile than in the top FIT tercile.[35] I then examine the interaction between BE/ME and institutional ownership in Model (2), which shows that consistent with Nagel (2005), the magnitude of value premium is decreasing in institutional ownership. Model (3) further put the interaction terms of BE/ME with both institutional ownership and FIT together. The interaction of FIT is -0.56% (t-stat -1.89), indicating that after controlling for the effect of institutional ownership, the value premium is 0.33% stronger the bottom FIT tercile than in the top FIT tercile.[36]

Model (4) further controls for the effect of firm size on the value premium by including its interaction term with BE/ME, where the effect of historical FIT on value premium is about the same as in Model (5), suggesting that the effect of FIT on value premium is robust to the control of the effect of firm size on the value premium. In the meantime, the interaction of firm size is not significant at the standard level, probably because my sample excludes the

[35] The value premium is measured by the difference in monthly return between the top and bottom BE/ME deciles, and the difference of 0.47% is calculated as 0.66 (difference in standardized lag FIT between top and bottom lag FIT terciles) times 0.9 (difference in standardized past returns between top and bottom BE/ME deciles) times -0.79, the coefficient of the interaction term.

[36] The value premium is measured by the difference in monthly return between the top and bottom BE/ME deciles, and the difference of 0.33% is calculated as 0.66 (difference in standardized lag FIT between top and bottom lag FIT terciles) times 0.9 (difference in standardized past returns between top and bottom BE/ME deciles) times -0.56, the coefficient of the interaction term.

small stocks with market capitalizations below NYSE 10% cutoff or prices below \$5.

Model (5) to (7) further examine the effects of FIB and FIS on the value premium by interacting BE/ME with FIB and FIS. Model (5) examines the interactions of BE/ME with FIB and FIS; Model (6) further controls for institutional ownership, and Model (7) controls for the effects firm size on the value premium. The results show that the FIS interactions are significant but the FIB interactions are insignificant. For example, in the full model of (7), the FIS interaction is -0.45 (t-stat -1.69) but the FIB interaction is -0.36 (t-stat -1.21). these results suggest that the effect of FIS on the value premium is stronger than the effect of FIB.

I also conduct sub-period analysis by splitting the sample period into three sub-periods: 1980-1987, 1988-1996, 1997-2005, each of these sub-periods containing eight or nine years. Next, I repeat the tests for the three sub-periods. To summarize, the sub-sample results are similar to full-sample results. An exception is that the effect of trader composition on the value premium does not hold for the sub-period of 1988-1996. For brevity, I list some major sub-sample results in Table 14 which presents the effect of trader composition on momentum), Table 15 which presents the effect of trader composition on PEAD), and Table 16 which presents the effect of trader composition on the value premium.

While Table 14 and Table 15 verify the effects of trading composition on momentum and PEAD in the sub-periods, Table 16 shows that the differences in the value premium between the top and bottom FIT tercile are significant for the sub-periods of 1980-1987 and 1997-2005 but insignificant for the sub-period of 1988-1996, which is 0.08% per month (t-stat 0.27). This inconsistency is caused by the fact the the overall value premium is weaker for my sample in the sub-period of 1988-1996. For example, the value premium is 0.36% (t-stat 1.22), 0.26% (t-stat 0.65) and 0.28% (t-stat 1.04) for the three FIT terciles respectively. Therefore the average poor performance of the value strategy leads to the indistinguishable cross-sectional difference between FIT terciles during this period. However, the effect of FIT on the value premium exists for the two other sub-periods where the value strategy does perform. To summarize, the sub-sample analysis of the value premium result is supportive to my hypothesis that the more severe pricing errors in the low FIT group leads to the stronger value premium in these stocks.

To summarize, this subsection presents strong empirical evidence that stocks with lower fractions of institutional volumes exhibit significantly larger value premium. Further evidence indicates that fraction of institutional sell volume has stronger effect on the value premium than does fraction of institutional buy volume. In addition, the stronger value premium in stocks dominated by individual traders is supportive of Lakonishok, Shleifer, and Vishny (1994), Daniel and Titman (1997) and Griffin and Lemmon (2002) which suggest that the value premium is associated with mispricing rather than risk.

In this chapter, I present significant relationships between trader composition and the cross-section of stock returns. Specifically, stocks with lower fractions of institutional volumes underperform stocks with higher fractions of institutional volumes, and this underperformance is more pronounced in liquid stocks. Moreover, stocks with lower fractions of institutional volumes exhibit stronger stock market anomalies such as return momentum, post earnings-announcement drift, and the value premium. Further analysis show that the aforementioned relationships comes mainly from the effect of institutional sell volumes.

Therefore this chapter presents evidence that institutional trading generally improves stock price efficiency. However, does it indicate that institutions improve price efficiency in every scenario? To address this question, the next chapter will analyze the effect of positive-feedback trading by institutions on stock return momentum and stock price efficiency.

2 Does Positive-Feedback Trading by Institutions Contribute to Momentum?

2.1 Measuring Positive-Feedback Trading by Institutions

Positive-feedback trading, or momentum trading, is simply the trading strategy of buying past winners and/or selling past losers. Such trading might be fostered by the incentive for institutions to 'window dress' or herd. Institutional preference or the belief that trends are likely to continue can also induce institutional positive-feedback trading.[37]

Although several previous studies suggest that institutions are positive-feedback traders, other studies find little evidence of positive-feedback trading by institutions.[38] These studies make different conclusions, yet they all treat stocks as a homogeneous group in terms of the intensity of institutional positive-feedback trading. However, the intensities of institutional positive-feedback trading could be vastly different across individual stocks. For example, if during a time period institutions, on one hand, buy stock i when its price rises and sell stock i when its price falls and, on the other, sell stock j when its price rises and buy stock j when its price falls, then institutions act as positive-feedback traders to stock i but contrarian traders to stock j. Consistent with the existence of heterogeneity in positive-feedback

[37] See Andreassen and Kraus (1990), Lakonishok, Shleifer, Thaler, and Vishny (1991), Lakonishok, Shleifer, and Vishny (1992), Bennett, Sias, and Starks (2003), and Sias (2004) for the possible reasons of institutional positive-feedback trading.

[38] See Lakonishok, Shleifer, and Vishny (1992), Grinblatt, Titman, and Wermers (1995), Nofsinger and Sias (1999), Bennett, Sias, and Starks (2003), and Griffin, Harris, and Topaloglu (2003) for supportive evidence of institutional positive-feedback trading. Also see Falkenstein (1996), Grinblatt and Keloharju (2000), and Gompers and Metrick (2001) for counter-evidence.

trading among individual stocks, Cohen, Gompers, and Vuolteenaho (2002) observe that institutions buy past winners with positive cash flow news but sell past winners without cash flow news, while Badrinath and Wahal (2002) find that institutions are positive-feedback traders when they initiate a long position but are not positive-feedback traders when they change a current position or terminate a position.

In order to address the heterogeneity of institutional positive-feedback trading among individual stocks, I construct a measure, MT (momentum trading), which aims at evaluating the intensity of positive-feedback trading by institutions to individual stocks. The MT measure is updated every quarter on a two-year rolling basis; that is, I calculate the MT measure for a stock with the stock's returns and quarterly institutional holdings during the two-year estimation period, and then apply the obtained MT measure to the subsequent quarter. For example, I calculate MT using the holdings and returns from the first quarter of 1980 to the last quarter of 1981, and then apply this MT to January, February and March of 1982.

The rolling-window estimation avoids the endogeneity problem. In addition, I choose a two-year rolling window out of two concerns: first, a longer window might be inappropriate because the pattern of institutional positive-feedback trading might change over a long time period; second, a shorter window might be inappropriate as well, because I want to examine institutional trading patterns based on a long enough sequence of trades. The empirical results are similar, however, when I choose one-year or three-year rolling windows as a robustness check.

The MT measure of stock i is calculated using the following equation:

$$MT_i = \sum_{t=1}^{8} \left(\frac{\triangle hold_{it}}{\sum_{t=1}^{8} |\triangle hold_{it}|} ppindex_{it} \right) \tag{5}$$

Where $\triangle hold_{it}$ is the change of aggregate institutional share holdings of stock i over quarter t divided by stock i 's total shares outstanding; $ppindex_{it}$ is a discrete index of past performance of stock i , which varies from -5 to 5 and ranks stock i 's performance in the six-month period up to the beginning of quarter t.

In particular, the MT measure is calculated with the following four steps as illustrated in Figure 1:

Step One: As shown in Figure 1 Panel A, for all the eight quarters of the two-year estimation window, I calculate $\triangle hold_{it}$ for quarter t. $\triangle hold_{it}$ is positive if institutions in aggregate buy stock i during quarter t and negative if they, in aggregate, sell stock i during quarter t. Next, I sum up the absolute values of all eight $\triangle hold_{it}$. The sum, $\sum_{t=1}^{8} |\triangle hold_{it}|$, represents the total absolute institutional trading of stock i during the estimation period.

Step Two: As shown in Figure 1 Panel B, for quarter t in the estimation period, I divide the quarterly institutional trading $\triangle hold_{it}$ by $\sum_{t=1}^{8} |\triangle hold_{it}|$, the total absolute institutional trading obtained in the previous step. The ratios $\frac{\triangle hold_{it}}{\sum_{t=1}^{8} |\triangle hold_{it}|}$, their absolute values adding up to 1 across the eight quarters, are positive (negative) when institutions in aggregate buy (sell) stock i during quarter t. In addition, this ratio takes a high absolute value if institutions, in aggregate, trade stock i in large volume during quarter t relative to the other quarters of the estimation period.

Step Three: As shown in Figure 1 Panel B, I then calculate for each quarter t the $ppindex_{it}$, a discrete index measuring the past performance of stock i. In particular, at the beginning of quarter t, stocks are sorted into 10 portfolios according to their past six-month returns. Then stock i is assigned a discrete $ppindex_{it}$ between -5 to 5 based on its past return portfolio as shown in Table 17. $ppindex_{it}$ is positive for past winners and negative for past losers.

Step Four: Following equation (1), for each quarter t, I multiply $\frac{\triangle hold_{it}}{\sum_{t=1}^{8}|\triangle hold_{it}|}$ by $ppindex_{it}$ to obtain $\frac{\triangle hold_{it}}{\sum_{t=1}^{8}|\triangle hold_{it}|}ppindex_{it}$. This product is positive for quarter t when institutions in quarter t buy a past winner or sell a past loser. On the contrary, this product is negative for quarter t if institutions in quarter t buy a past loser or sell a past winner. Moreover, the product takes a big value if in this quarter institutions trade an extreme winner or extreme loser in large volumes. I then sum up the product across each quarter to obtain the MT measure for stock i. Based on this construction the MT measure, ranging between -5 and 5, is higher for stock i if during the estimation period institutions more often buy (sell) it when it is a past winner (loser).

To further understand the MT measure, consider two extreme examples. Suppose institutions are positive-feedback traders to stock i and contrarian traders to stock j. Suppose further that institutions trade both stocks twice during the two-year estimation period, buying stock i in quarter 3 when it is an extreme past winner ($ppindex_{i3}$ equals 5) and selling stock i in quarter 7 when it is an extreme past loser ($ppindex_{i7}$ equals -5). Conversely, institutions buy stock j in quarter 2 when it is an extreme past loser ($ppindex_{j2}$ equals -5) and sell stock j in quarter 4 when it is an extreme past winner ($ppindex_{j4}$ equals 5). As a result, for stock i, the product terms $\frac{\triangle hold_{it}}{\sum_{t=1}^{8}|\triangle hold_{it}|}ppindex_{it}$ are positive for quarter 3 and 7 but zero for the rest of the quarters. Since the absolute values of coefficients $\frac{\triangle hold_{it}}{\sum_{t=1}^{8}|\triangle hold_{it}|}$ sum up to 1, the two products sum up to 5. That is, MT_i equals 5, reflecting strong positive-feedback trading to stock i. Similarly, stock j's product terms $\frac{\triangle hold_{jt}}{\sum_{t=1}^{8}|\triangle hold_{jt}|}ppindex_{jt}$ are negative for quarter 2 and 4 but zero for the rest of the quarters. Since the absolute values of coefficients $\frac{\triangle hold_{jt}}{\sum_{t=1}^{8}|\triangle hold_{jt}|}$ sum up to 1, the two products sum up to -5, reflecting strong contrarian trading.

The MT measure distinguishes individual stocks according to how much institutional positive-feedback trading they experience. Therefore I can directly examine the impact of institutional positive-feedback trading on return momentum by comparing the profits of momentum trading strategy across MT levels. The MT measure also makes it possible for us to directly investigate the relationships between the effects of institutional positive-feedback trading and the effects of other factors on return momentum by calculating momentum profits for portfolios that are two dimensionally sorted on MT and other factors.

2.2 The Effect of Positive-Feedback Trading by Institutions on Return Momentum

2.2.1 The MT Measure and Firm Characteristics

I estimate the MT measure as described in Section 2.1 and report the summary statistics. Table 18 provides a snapshot of one quarter in every three years together with the summary statistics of the whole sample period. Although 13f institutional holding data start from the first quarter of 1980, the MT measure is available from the first quarter of 1982 because of the two-year rolling estimation method.

My sample contains $367,337$ firm-quarter observations with available MT

measures. The sample size increases from $2,552$ firms in the first quarter of 1982, to $4,499$ firms in the first quarter of 2003, reflecting the rapid growth of institutional trading over the past two decades. The average MT measures of the whole sample period and every quarters in Table 18 are significantly positive. An unreported result shows that the average MT measures are significantly positive at the 0.01 level for all of the 96 quarters during the 1982-2005 sample period, which indicates that institutions in aggregate are positive-feedback traders. However, although the mean MT measure is statistically significant, the economic significance is much weaker as the means and the medians of MT in all 96 quarters of the sample period are below 1. This result indicates that although institutions are positive-feedback traders, the average intensity of their positive-feedback trading behavior is rather weak. On average, the intensity of institutional positive-feedback trading during 1982-2005 is comparable to a strategy of buying (selling) the past winner (loser) stocks whose past returns are only slightly above (below) the median past stock returns but still within the middle past return quintile.

Although the summary statistics of MT are persistent over time, there are significant cross-sectional variations in MT during the sample period. For example, in the first quarter of 1982, the mean MT is 0.31 with a standard deviation of 2.16. The cutoff points also suggest significant cross-sectional dispersions: the 10% cutoff is -2.62; the 25% cutoff is -1.27; the 75% cutoff is 1.87 and the 90% cutoff is 3.52. These results suggest that different stocks are indeed subject to different amounts of positive-feedback trading by institutions.

One interesting question is how institutional positive-feedback trading is related to firm characteristics. For example, Lakonishok, Shleifer, and

Vishny (1992) observe stronger positive-feedback trading by pension funds in small stocks. In addition, Grinblatt, Titman, and Wermers (1995) find that positive-feedback trading by mutual funds is stronger on the buy side than on the sell side, implying that winner stocks experiences more positive-feedback trading than does losers.

In order to examine the relationships between institutional positive-feedback trading and firm characteristics, I calculate for each month the average firm characteristics of MT quintiles and report in table 19 the time-series means and t-statistics of the cross-sectional averages. The firm characteristics include monthly stock return, size, the book-to-market ratio (henceforth BE/ME), turnover, analyst coverage, return volatility, and firm age. I examine these firm characteristics because they are documented to affect stock return momentum. Firm size is the natural log of a firm's market capitalization. BE/ME is the summation of book equity and deferred tax of a firm divided by its market equity. I apply BE/ME calculated at the fiscal year end of year t to the one-year period starting from July of year $t+1$. Turnover is the monthly trading volume divided by total shares outstanding. Analyst coverage is the number of analysts providing a firm's one year earnings forecasts. Because trading volumes of NASDAQ stocks are inflated relative to those of NYSE/AMEX stocks, I follow Chen, Hong, and Stein (2002) to demean the turnovers with the cross sectional averages of NASDAQ or NYSE/AMEX turnovers according to the stock market in which the firms are listed.[39] I also follow Griffin and Lemmon (2002) to adjust a firm's analyst coverage by the average coverage of the NYSE size quartile that the firm belongs to.[40] I calculate return volatility and firm age following Jiang,

[39]Unless otherwise specified, all the turnovers in this paper are demeaned turnovers.

[40]Unless otherwise specified, all the analyst coverages in this paper are residual analyst coverages. My results are not changed when I use another size-adjusted analyst coverage

Lee, and Zhang (2005) and Zhang (2006). In particular, for month t, return volatility is the standard deviation of daily stock returns of 25 trading days up to the end of month t-1. Age of a firm is the number of months from the firm's first CRSP monthly return record.

Table 19 presents three results on the relationships between institutional positive-feedback trading and firm characteristics:

First, consistent with Lakonishok, Shleifer, and Vishny (1992), high MT stocks are relatively small in size. The average firm size of the top MT quintile is 19.96, lower than those of the middle three quintiles. In the meantime, low MT stocks are also relatively small in size, with an average firm size of 19.78. Second, there is no discernable difference in the levels of institutional positive-feedback trading between winner stocks and loser stocks. For example, the average monthly returns of the top MT quintile is 1.01%, not significantly different from 1.17%, the average returns of the bottom MT quintile. One possible reason of the difference between my finding and Grinblatt, Titman, and Wermers (1995) is that my sample includes all institutions while their samples include only mutual funds. Third, the strength of institutional positive-feedback trading is related to turnover, BE/ME, analyst coverage, return volatility and firm age. Table 19 shows that institutional positive-feedback trading level increases in turnover and return volatility and decreases in BE/ME, coverage and firm age. The differences in turnover, BE/ME, analyst coverage, return volatility and firm age between the top and the bottom MT quintiles are 0.12, 0.05, -0.79, 0.004 and -53, all statistically significantly at the standard level.

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measure suggested by Hong, Lim, and Stein (2000).

2.2.2 Institutional Positive-Feedback Trading and Return Momentum

This subsection examines the effect of institutional positive-feedback trading on stock return momentum. I independently sort stocks into three groups of MT and ten groups of past performance and then calculate, for each MT groups, the momentum profits of the six-month formation/six-month holding strategy following Jegadeesh and Titman (2001).[41] In particular, at the beginning of every month, I form two-dimensional portfolios on the MT measures and the past six-month cumulative stock returns and hold these portfolios for six months.

The result is reported in Table 20 Panel A, which shows that momentum profits increase in the MT measures, ranging from 1.08% (t-stat 2.95) for the bottom MT tercile to 1.61% (t-stat 4.72) for the top MT tercile. The difference in momentum profits between the top and the bottom MT terciles is 0.53% (t-stat 3.21), significant at the 0.01 level. The difference is not only statistically significant but economically significant as well, compounding to an annual return difference of 8.58%.

For a robustness check, I further report in Panel B the results of Fama-French three-factor regressions of momentum profits. The difference in the three-factor alphas between the top and bottom MT terciles is 0.48% (t-stat 3.02), close to the difference in momentum profits reported in Panel A. To summarize, Table 20 presents strong empirical evidence that institutional positive-feedback trading contributes to stock return momentum.

[41] I also repeat the tests in this paper with an alternative momentum strategy that skips a month between formation and holding period. The results are not changed with the skip-a-month momentum strategy.

Trading cost is always a concern when we evaluate the profitability of a trading strategy. If, for example, employing momentum strategy to high MT stocks is associated with much higher transaction costs than to low MT stocks, then the difference in transaction costs could offset the difference in momentum profits. Although the data of transaction costs are not directly available, we could evaluate the transaction costs based on firm characteristics across MT levels. Specifically, if we consider size and turnover as proxies for liquidity and hence trading cost, then the trading costs of applying momentum strategies to high MT stocks should be no higher than that of low MT stocks because as shown in Table 19, high MT stocks are only slightly smaller in firm size but much higher in turnover than low MT stocks.

2.2.3 Robustness Check with Firm Size, BE/ME and Turnover

Three most important firm characteristics, size, BE/ME and turnover, have been documented to have considerable impact on return momentum. For example, Hong, Lim, and Stein (2000) and Jegadeesh and Titman (2001) observe stronger return momentum in small stocks than in large stocks. Daniel and Titman (1999) shows that return momentum is stronger in low BE/ME stocks than in high BE/ME stocks. Lee and Swaminthan (2000) find that return momentum is more prevalent for the stocks with higher turnover.

This subsection is intended to check whether the effect of institutional positive-feedback trading on return momentum is robust after controlling for size, BE/ME and turnover. In addition, it is also interesting to understand the relationships between the effect of institutional positive-feedback trading and those of size, BE/ME or turnover on return momentum.

I conduct the tests in this regard by calculating the profits of the six-month formation and six-month holding momentum strategy for stock portfolios two-dimensionally sorted on the MT measure and size, or BE/ME, or turnover. In particular, at the beginning of month t, I independently sort stocks into three groups of MT, three groups of size, BE/ME or turnover, and five groups of past six-month cumulative returns.[42] Then all these three-dimensional portfolios are held for six months. This momentum strategy is the same as in Jegadeesh and Titman (2001) except that I form five groups of past returns instead of ten groups in order to ensure enough number of stocks in each three-dimensional portfolio.

Panel A of Table 21 reports average monthly returns of the three-dimensional portfolios sorted on size, MT and past return, while Panel B provide a comparison of the momentum profits (W-L) for the three by three size-MT groups. Within all three size groups, momentum profits are increasing in the MT measure. Specifically, the differences in monthly momentum profits between high and low MT stocks are 0.45% (t-stat 2.73), 0.38% (t-stat 2.38) and 0.44% (t-stat 2.22), all statistically significant at the standard levels. To summarize, Table 21 shows that the effect of institutional positive-feedback trading on return momentum persists after controlling for firm size.

One might attribute the result in Table 21 to the variation of size within each size group. To address this concern, I report the average decile ranks of size and MT for each size-MT group in Table 21 Panel A. In particular, I first assign decile ranks of size and MT to the stocks in each cross-section, where 1 is assigned to the bottom decile and 10 to the top decile. Next, I calculate the time series-averages of the cross sectional means of size and MT

[42] Size is measured at the end of month t-1. I match BE/ME at the fiscal year end of year t-1 to the one-year period starting from July of year t+1. Turnover is the demeaned turnover of month t-1.

ranks for each size-MT group. As shown in Panel A, within each size group the size-MT groups are almost undistinguishable in size but vastly different in MT, indicating that the difference in momentum profits between the high and low MT group is driven by the variation in MT rather than firm size.

In addition, Panel B shows that the effect of firm size on stock return momentum is also robust after controlling for institutional positive-feedback trading. For example, the differences in monthly profits between large and small stocks across MT groups are 0.62% (t-stat 3.60), 0.35% (t-stat 1.89) and 0.63% (t-stat 2.99), all statistically significant at the standard levels. These results indicate that the effects of firm size and institutional positive-feedback trading on return momentum are independent of each other.

Similarly, Table 22 examine the effect of institutional positive-feedback trading on stock return momentum after controlling for BE/ME. Panel A reports and Panel B compares the momentum profits across the MT-BM groups. We can see in Panel B that within two of the three BE/ME groups, the differences in momentum profits between high and low MT stocks are economically and statistically significant. In particular, the differences in monthly momentum profits between high and low MT stocks are 0.74% (t-stat 4.00), 0.23% (t-stat 1.28) and 0.41% (t-stat 2.02). Although one of the difference 0.23% is not statistically significant, the other difference 0.74% is not only statistically significant at the 0.01 level but also much higher than 0.53%, the average effect of MT as shown in Table 20. Therefore, the results of Table 22 verify that the effect of institutional positive-feedback trading is robust to the control of BE/ME.

In order to address the concern that the result might be due to the variation of BE/ME within each BE/ME group, I also calculate the average decile ranks of BE/ME and MT for each BM-MT portfolio. Specifically, I first assign decile ranks of BE/ME and MT to the stocks in each cross-section, where 1 is assigned to the bottom decile and 10 to the top decile. Next, I calculate the time series averages of the cross sectional means of the ranks. Panel A shows that within each BE/ME group, there is no discernable difference in BE/ME but vast difference in MT between the BM-MT groups, indicating that the differences in momentum profits between high and low MT groups are caused by the variation of institutional momentum trading rather than BE/ME.

In addition, Table 22 Panel B shows that the effect of BE/ME on stock return momentum is also robust after controlling for institutional positive-feedback trading. For example, the differences in monthly momentum profits between the low BE/ME and the high BE/ME stocks for the three MT groups are 0.19% (t-stat 0.93), 0.54% (t-stat 2.54) and 0.51% (t-stat 2.22), respectively.

Last, Table 23 presents the robustness check which controls of turnover. Panel A reports the average monthly returns of each three-dimensional portfolios sorted on turnover, MT, and past return, while Panel B presents the momentum profits across turnover-MT groups. We can see that within all three turnover groups, momentum profits are increasing with MT level and the differences in momentum profits between high and low MT stocks are statistically significant two out of the three turnover groups. In particular, the differences in monthly momentum profits between high and low MT stocks are 0.12% (t-stat 0.78), 0.32% (t-stat 2.38) and 0.59% (t-stat 3.57). To summarize, Table 23 shows that the contribution of institutional positive-feedback trading to stock return momentum persists after controlling for turnover.

I also report in Panel A the average decile ranks of turnover and MT for each turnover-MT portfolio, which show that within each turnover group, the turnover-MT groups are almost undistinguishable in turnover but vastly different in MT. This result indicates that the difference in momentum profits between high and low MT groups is driven by institutional positive-feedback trading rather than turnover. Panel B shows the coexistence of the effects of turnover and institutional positive-feedback trading on stock return momentum. For example, the difference in monthly profits between high turnover and low turnover stocks are 0.31% (t-stat 1.64), 0.51% (t-stat 2.85) and 0.77% (t-stat 3.87), all statistically significant at the standard levels.

2.2.4 Robustness Check With The Residual MT Measures

One might argue that the sub-portfolio analysis based on three-dimensional sorts in Table 21 to Table 23 is incomplete in the sense that they control for size, BE/ME and turnover separately, and that the effect of the MT measure could be altered if these factors are controlled simultaneously. An ideal test to address this concern is to sort stocks independently on size, BE/ME, turnover, and MT, and then examine momentum profits across this multi-dimensionally sorted portfolios. However, this method will require a huge sample size. For example, if in each cross-section we sort stocks into three groups based on each of the aforementioned four variables and five groups based on past returns, in total 405 sub-portfolios will be generated, leaving very few or even no stocks in some portfolios given the current sample size.

In order to control for size, BE/ME and turnover simultaneously, I create a residual MT measure, $ResMT1$. The methodology is similar to Hong, Lim, and Stein (2000) in a different context. Specifically, in each month t of the sample period, I estimate a cross-sectional regression of the MT measure on firm size, BE/ME, and demeaned turnover of month t-1. I then take the residuals from these regressions as the $ResMT1$ measures, which is the component of MT measures that is orthogonal to size, BE/ME and turnover.

Next, I repeat the test of Table 20 but with the $ResMT1$ measure rather than the original MT measure. In particular, at the beginning of every month, I form three by ten two-dimensional portfolios independently on the $ResMT1$ measures and the past six-month cumulative stock returns and hold these portfolios for six months.

The result is reported in Table 24 Panel A, which shows that momentum profits increase in the $ResMT1$ measures, ranging from 0.93% (t-stat 2.42) for the bottom $ResMT1$ tercile to 1.50% (t-stat 4.17) for the top $ResMT1$ tercile. The difference in momentum profits between the top and the bottom $ResMT1$ terciles is 0.57% (t-stat 3.24), significant at the 0.01 level. Panel B further report the Fama-French three-factor alphas for momentum profits of the three $ResMT1$ groups. The difference in the three-factor alphas between the top and bottom $ResMT1$ terciles is 0.48% (t-stat 2.87). To summarize, Table 24 shows that the effect the MT measure on return momentum is robust when we control for size, BE/ME and turnover simultaneously.

Besides size, BE/ME and turnover, three other firm characteristics were also found to affect return momentum. Specifically, Hong, Lim, and Stein (2000) shows that return momentum is stronger in stocks with lower analyst coverage. Jiang, Lee, and Zhang (2005) and Zhang (2006) document stronger momentum in firms with higher return volatility and shorter history. In order to further control for analyst coverage, return volatility and firm age, I create a second residual MT measure, ResMT2. In particular, in each month t of the sample period, I estimate a cross sectional regression of the MT measure on firm size, BE/ME, demeaned turnover, residual analyst coverage of month t-1, return volatility in the 25 trading days up to the end of month t-1, and firm age of month t-1.[43] The $ResMT2$ measures are the residuals from these regressions.

Next, I repeat the test in Table 24 with the $ResMT2$ measure rather than the $ResMT1$ measure. In particular, I form three by ten two-dimensional portfolios independently on the $ResMT2$ measures and the past six-month cumulative stock returns and hold these portfolios for six months. Table 25 Panel A shows that momentum profits increase in the $ResMT2$ measures, ranging from 0.96% (t-stat 2.52) for the bottom $ResMT2$ tercile to 1.45% (t-stat 4.02) for the top $ResMT2$ tercile. The difference in momentum profits between the top and the bottom $ResMT2$ quintile is 0.49% (t-stat 2.89), significant at the 0.01 level. Panel B further shows that the difference in the three-factor alphas between the top and bottom $ResMT2$ terciles is 0.42% (t-stat 2.52). These results suggest that the effect of the MT measure persists after further controlling for analyst coverage, return volatility and firm age.

2.2.5 Robustness Check with An Alternative Measure of Positive-Feedback Trading

In this subsection I further examine the robustness of the effect of institutional positive-feedback trading with an alternative positive-feedback trading measure. In particular, in equation (1) that describes the estimation of the

[43]The estimation of return volatility and firm age is the same as in Jiang, Lee, and Zhang (2005), and Zhang (2005).

MT measure, I adjusted quarterly institutional trading, $\triangle hold_{it}$, by total institutional trading during the estimation period, $\sum_{t=1}^{8} |\triangle hold_{it}|$. Since the adjusted quarterly institutional trading $\frac{\triangle hold_{it}}{\sum_{t=1}^{8} |\triangle hold_{it}|}$ add up to 1 across the eight quarters during estimation period, MT measure ranges between -5 and 5. This nice property of the MT measure enable us to easily assess the intensity of institutional positive-feedback trading by the value of the MT measure. For example, a MT measure of 4 indicates that the intensity of institutional positive-feedback trading is comparable to a strategy of buying past winners in the second highest past return decile (ppindex equals 4) and/or sell past losers in the second lowest past return decile (ppindex equals -4).

While the aforementioned adjustment of total institutional trading make the MT measure easily interpreted, it results in a disadvantage that the MT measure does not capture the magnitude of total institutional trading. For example, suppose institutions are positive-feedback traders to both stock i and stock j. Suppose further that institutions trade both stocks twice during the two-year estimation period. In particular, they buy 1% of stock i's total shares outstanding in quarter 3 when it is an extreme past winner ($ppindex_{i3}$ equals 5) and sell 1% of stock i in quarter 7 when it is an extreme past loser ($ppindex_{i7}$ equals -5). In addition, institutions buy 2% of stock j's shares in quarter 3 when it is an extreme past winner and sell 2% of stock j in quarter 7 when it is an extreme past loser. Then for stock i, the product terms $\frac{\triangle hold_{it}}{\sum_{t=1}^{8} |\triangle hold_{it}|} ppindex_{it}$ are 2.5 (0.5 times 5) for quarter 3 and 7 but zero for the rest of the quarters, resulting in a MT measure of 5 for stock i. Stock j's product terms $\frac{\triangle hold_{jt}}{\sum_{t=1}^{8} |\triangle hold_{jt}|} ppindex_{jt}$ are also 2.5 (0.5 times 5) for quarter 3 and 7 but zero for the rest of the quarters, leading to a MT measure of 5 for stock j. Although the MT measures of stock i and j are both 5, institutional positive-feedback trading could have stronger impact on stock j than stock i because institutions trade stock j in bigger volume than they trade stock i. In order to address this concern, I construct an alternative measure of institutional positive-feedback trading, the $MTWO$ measure (MT measure without adjustment), following the equation below.

$$MTWO_i = \sum_{t=1}^{8} (\triangle hold_{it} \times ppindex_{it}) \tag{6}$$

The $MTWO$ measure is constructed with the same method as the MT measure except that I do not adjust quarterly institutional trading, $\triangle hold_{it}$, with total institutional trading during the estimation period, $\sum_{t=1}^{8} |\triangle hold_{it}|$. As a result, the $MTWO$ measures captures the magnitudes of institutional trading.

I calculated the $MTWO$ measure following equation (2) and examine its correlation with the MT measure. The Spearman rank correlation is as high as 0.87, indicating that the $MTWO$ measure and the MT measure are strongly correlated. Next, I repeat the test in Table 20 but with the $MTWO$ measure rather than the original MT measure. The result is reported in Table 26 Panel A, where momentum profits increase from 1.06% per month (t-stat 2.93) for the bottom $MTWO$ tercile to 1.55% per month (t-stat 4.57) for the top $MTWO$ tercile. The difference in momentum profits between the top and the bottom $MTWO$ terciles is 0.49% (t-stat 2.94), significant at the 0.01 level. Panel B further report the Fama-French three-factor alphas for momentum profits of the three $MTWO$ groups. The difference in the three-factor alphas between the top and bottom $ResMT1$ terciles is 0.45% (t-stat 2.76). To summarize, Table 26 shows that the effect institutional positive-feedback trading on return momentum is robust with the alternative measure that considers the magnitudes of institutional trading.

2.3 Institutional Positive-Feedback Trading and Stock Price Efficiency

This section aims at investigating the effect of institutional positive-feedback trading on stock price efficiency. Theoretically it is not clear whether or not institutional positive-feedback trading improves the market efficiency. On one hand, institutional positive-feedback trading could improve market efficiency if it speeds up the correction of stock mispricing. Specifically, if market underreact to positive (negative) news and thus underprice (overprice) the past winners (losers), then institutional positive-feedback trading can speed up the price adjustment process by pushing the winners (losers) further to the 'correct' level. On the other hand, institutional positive-feedback trading could deteriorate market efficiency by driving stock prices further away from their fundamentals if such trading is unrelated to information on firm fundamentals or is induced by overreaction.

2.3.1 Evidence from Earnings Revision

Perhaps the most important information regarding stock prices is earnings information. Chan, Jegadeesh, and Lakonishok (1996) observe the coexistence of return momentum and earnings momentum, namely, both past stock return and past accounting performance predict future stock returns. They examine revisions of earnings analyst forecasts across past return levels during the one-year post-ranking period, and find that post-ranking earnings revisions are more favorable for past winners than for past losers. An international study by Hong, Lee, and Swaminathan (2003) studies eleven equity markets and find that stock return momentum only exists in the markets where earnings momentum is profitable, indicating that stock return momentum and earnings momentum share the same information dissemination system.

Post-ranking earnings revision provides us with an ideal test vehicle not only because earnings revision has implication on stock mispricing but also because earnings revision, unlike stock return, is exogenous to institutional trading. Under the hypothesis that institutional positive-feedback trading improves the market efficiency, high MT past winners (losers) are more underpriced (overpriced) than low MT past winners (losers), and institutional positive-feedback trading helps adjust stock prices to their 'correct' levels by creating stronger momentum in high MT stocks. Therefore, in this case we expect to observe that by positive-feedback trading, institutions buy (sell) the past winners (losers) that will experience more favorable (unfavorable) earnings revision during the post-ranking period than other past winners (losers). As a result, if institutional positive-feedback trading improves the market efficiency, we would expect the biggest difference in post-ranking earnings revision between past winners and past losers to appear in the top MT quintile. In other words, in this scenario the bigger return difference between high MT past winners and past losers should be justified by the stronger market underreaction and hence bigger difference in post-ranking earnings revision.

Following Chan, Jegadeesh, and Lakonishok (1996) and Hong, Lee, and Swaminathan (2003), I use the average one-year earnings forecasts in this study and calculate earnings revision following the formula below.

$$ER_{it} = \frac{(EF_{it} - EF_{it-1})}{P_{it-1}} \tag{7}$$

Where ER_{it} is earnings revision of firm i from month $t-1$ to month t; EF_{it} and EF_{it-1} are the mean earnings forecasts of firm i in month t and $t-1$, respectively; P_{it-1} is the stock price of firm i at the end of month $t-1$. ER_{it} is positive if analysts on average raise the earnings forecasts of firm i from month $t-1$ to month t and negative if they adjust the forecasts downwards.

One issue of equation (3) is that the mean forecasts before and after an announcement date cover different fiscal years. To address this issue, when a firm announces earning in month t, I treat earnings revision around month t following Hong, Lee, and Swaminathan (2003): if the earnings announcement date is before the I/B/E/S summary date, then earnings revision of month t is calculated as the difference between mean one-year earnings forecast of month t and mean two-year earnings forecast of month $t-1$ divided by the stock price at the end of month $t-1$. On the other hand, if the earnings announcement date is after the I/B/E/S summary date, then earnings revision of month t is still calculated following equation (3) but earnings revision of month $t+1$ is calculated as the difference between mean one-year earnings forecast of month $t+1$ and mean two-year forecast of month t divided by the stock price at the end of month t.

I begin by sorting stocks independently into quintiles of MT and past six-month returns and examine the average earnings revisions during the one-year period after portfolio formation. In particular, at the beginning of month t, I independently sort stocks into quintiles of the MT measures as well as cumulative returns in the past six months. Next, I examine the average earnings revisions for each month in the one-year period starting from t and report the results in Panel A of Table 27.

Consistent with Chan, Jegadeesh, and Lakonishok (1996), most of the mean earnings revisions are negative, revealing the fact that initially over-optimistic analysts gradually adjust their forecasts downwards to the 'correct' level. Moreover, within each MT quintile, earnings revisions are more favorable for winner stocks than for loser stocks in every of the twelve months after portfolio formation, indicating market underreaction.

In order to examine whether institutional positive-feedback trading improves market efficiency, I compare the differences in earnings revisions between winners and losers for the top and bottom MT quintiles and report the results in Panel B. Table 27 Panel B shows that in five out of the twelve months, the differences in earnings revisions between winners and losers are actually smaller in the top MT quintile than in the bottom MT quintile. Although the other seven of the twelve differences are positive, none of them is significant at the standard levels.

Table 27 reveals that the stronger momentum generated by institutional positive-feedback trading is not accompanied by the bigger difference in the post-ranking earnings revision between winners and losers. Therefore, the evidence from earnings revision is *inconsistent* with the hypothesis that institutional positive-feedback trading improves market efficiency.

2.3.2 Evidence from Long-Term Reversal of Momentum Profits

Extant research has observed that momentum profit reverts one year after portfolio formation, which suggests that return momentum results from mispricing instead of risk.[44] When the prices of winners and losers start to converge back to the levels that correctly reflect firm fundamentals, momentum profit reverts.

Interestingly, the model of Hong and Stein (1999) predicts that stocks that attract more positive-feedback trading will experience deeper long-term reversal in momentum profits. This occurs in their model because the positive-feedback traders push the past winners further up and beat the past losers further down, thereby driving stock prices even further away from their fundamentals. This claim is consistent with the hypothesis that institutional positive-feedback trading hampers market efficiency. If, on the contrary, institutional positive-feedback trading improves market efficiency and drives the prices of underpriced (overpriced) winners (losers) further to their fundamental values, then we would expect no difference in the long-term reversals of momentum profits for the stocks that experience different amount of institutional positive-feedback trading.

In order to examine the long-term reversals across different levels of institutional positive-feedback trading, I sort stocks into MT quintiles and examine the magnitudes of long term reversals in their momentum profits. In particular, at the beginning of month t, I form five by five portfolios independently on the MT measure and past six-month stock returns, and calculate cumulative momentum profits (winners minus losers) for each MT quintile up to each month in the three-year period from month t.

Table 28 reports the results. First, consistent with previous studies, within each MT quintile the cumulative momentum profits peak in the twelfth month after portfolio formation and then slowly drift downwards.

[44]See, for example, Jegadeesh and Titman (2001) for the analysis of long term reversal in momentum profit.

The right most column reports the change in cumulative momentum profits from the twelfth month to the thirty-sixth month. All the changes are negative, reflecting long-term reversals in momentum profits.

Second, the pattern of long term reversals across different MT levels is evident: the magnitudes of the reversals are increasing with MT level, from -3.44% of the bottom MT quintile to -6.36% of the top MT quintile. This result indicates that stocks that receive more institutional positive-feedback trading experience much stronger reversals in momentum profits than stocks lack of institutional positive-feedback trading.

In order to provide a clear view of this pattern, I plot long-term cumulative momentum profits of the top and bottom MT quintile during the three-year post-formation period. Figure 2 shows very clearly that the top MT quintile exhibits much deeper reversal than the bottom MT quintile: although returns of the top MT quintile reaches a much higher peak than that of the bottom MT quintile, the two return sequences reach approximately the same low levels three years after portfolio formation.

To summarize, this subsection shows that stocks subject to stronger institutional positive-feedback trading exhibit much deeper long-term reversal in momentum profits during the three-year post-ranking period. This result is consistent with hypothesis that institutional positive-feedback trading hampers market efficiency.

2.3.3 The Relationship Between MT and FIT Measures

Chapter one presents evidence that higher fraction of institutional trading volume leads to greater price efficiency and therefore lower momentum. This result suggests that institutions act as rational traders in generals. Chapter two shows that although institutions are in general rational traders, their particular trading behaviors could still hamper price efficiency. For example, when institutional act as positive-feedback traders, their trend-chasing behavior intensifies momentum and therefore hampers price efficiency. Since both the MT measure and the FIT measure affect the magnitudes of momentum, I examine the relationship of these two measures.

First, I calculate the correlation between the FIT measure and the MT measure, which is as low as 0.005, indicating that the two measures are not correlated. This results show that stocks with higher fraction of institutional trading volume are not the stocks subject to stronger institutional positive-feedback trading. This result is consistent with the discussion in the dissertation that the effect of positive-feedback trading on momentum is not necessarily the evidence that institutions overall hamper price efficiency because positive-feedback trading is only one of the many institutional trading strategies.

Second, I calculate the momentum profits across the stocks two-dimensionally sorted on the FIT measure and the MT measure. In particular, At the beginning of month t, I independently sort stocks into three groups of the MT measures, three groups of one-quarter lag FIT measures, and quintiles of cumulative returns over the six-month period up to the end of month t-1. Following the six-month holding/six-month formation strategy of Jegadeesh and Titman (2001), I hold these three-dimensionally sorted portfolios for six months.

Table 29 Panel A reports the average monthly returns of the portfolios and Panel B reports the comparisons of momentum profits across the FIT-

MT groups. The results show that the effects of the FIT measure and the MT measure on stock return momentum are independent of each other.

3 Conclusion

My dissertation studies the the effects of institutional trading on stock price efficiency. I find that institutional trading has significant yet complicated impact on price efficiency. In particular, institutional trading in general improves price efficiency. For example, major stock market anomalies such as stock return momentum, post earnings announcement drift, and the book-to-market effect are much stronger in stocks with lower institutional trading volume. However, some institutional trading behaviors could hamper stock price efficiency even though institutions are generally rational arbitrageurs. Specifically, I show that when institutions act as positive-feedback traders, their trading contributes to stock return momentum and hampers prices efficiency.

Figures

Figure 1: Fitted Distributions of Earnings-Announcement Returns Across FIT Levels

This table presents the fitted distributions of the four-day returns around earnings-announcements across FIT levels. I calculate the four-day market model adjusted abnormal returns around quarterly earnings announcements for the sample firms. Then for each month, I sort firms with quarterly earnings-announcements in that month into deciles of one-quarter lag FIT. I then pool the earnings-announcement returns for each FIT decile, fit these returns into normal distribution, and plot the distributions across the FIT deciles. FitRank1 represents the bottom FIT decile, FitRank4 represents the 4th FIT decile, FitRank7 represents the 7th FIT decile, and FitRank10 represents the top FIT decile.

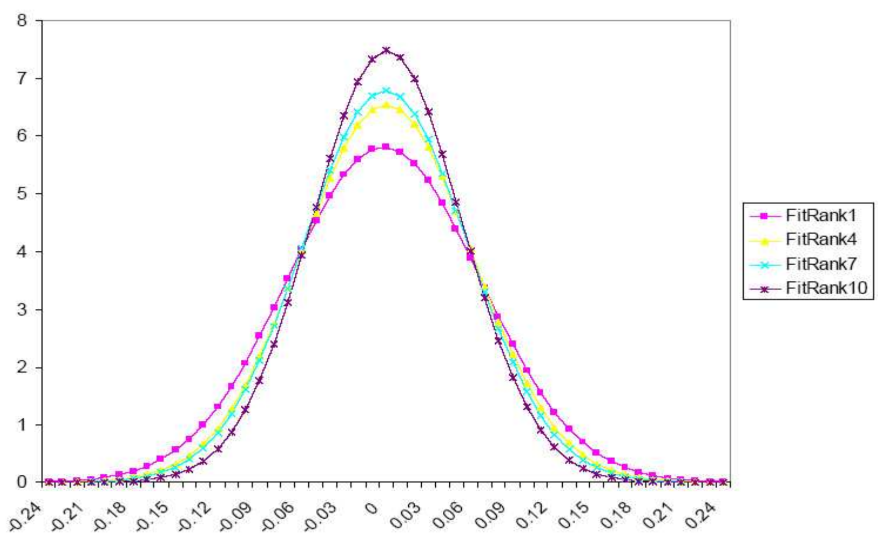
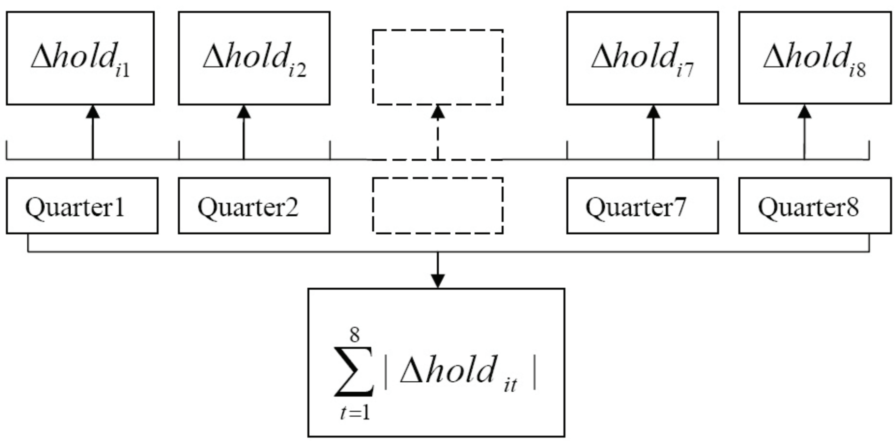


Figure 2: Construction of the MT Measure

This figure illustrates the first three steps of constructing the MT measure. There are in total eight quarters in the estimation period. I first calculate institutional trading in each of the eight quarters and then sum up the absolute value of the quarterly trading as shown in Panel A. Next, for each quarter of the two-year estimation period, I calculate past performance index (PPindex) and weight of the trading as shown in Panel B.

Panel A: Step One



Panel B: Step Two and Three

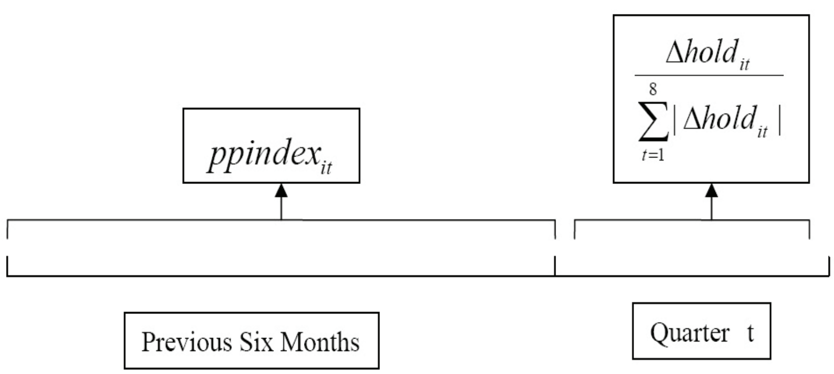
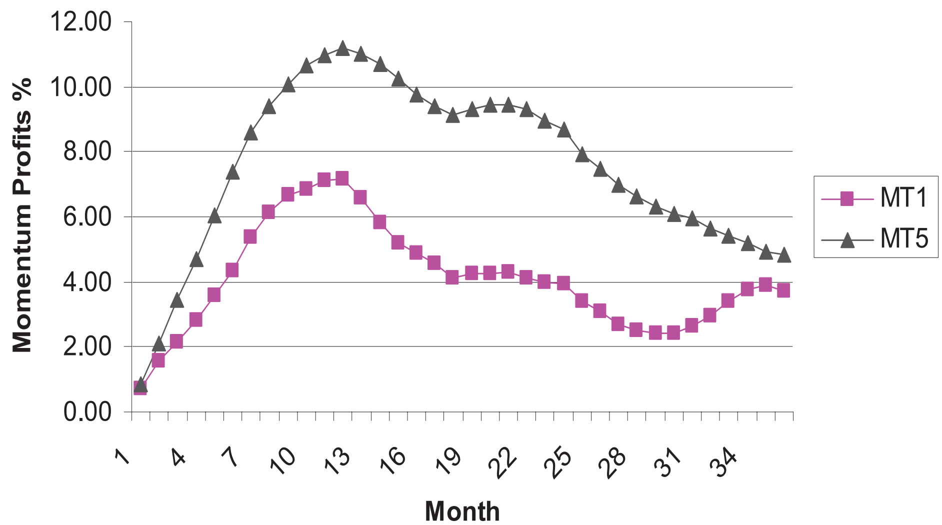


Figure 3: Long-Term Momentum Profits Across MT Quintiles

This figure presents the long term momentum profits of the top (MT5) and bottom (MT1) quintiles of the MT measure. At the beginning of month t, I independently sort stocks into quintiles of the MT measures and past six months' cumulative stock returns. I then calculate within each MT quintile the cumulative momentum profits (winners minus losers) up to each month during the three-year post-ranking period. Returns are in the scale of percentages.



Tables

Table 1: Summary Statistics

This table summarizes FIT, FIB, FIS as well as firm characteristics of the sample, which contains 236,908 firm-quarters during 1980 to 2005. FIT, FIB and FIS are calculated following equations (1) to (6) in the paper. Betas of individual stocks are obtained from CRSP; Size is the natural log of a firm's market capitalization; BM/ME is calculated as the summation of a firm's book equity and deferred tax divided by the firm's market equity; past return is the cumulative return of a firm during the past six months. The residual analyst coverage is calculated following Griffin and Lemmon (2002) by subtracting the average analyst coverage of the NYSE size quartile of a firm from the firm's analyst coverage. Turnover is the total quarterly turnover calculated as the summation of the monthly turnovers during the quarter, where monthly turnover is obtained by dividing the total trading volume of a firm by its total shares outstanding. Idiosyncratic volatility is the monthly updated volatility of residuals from the Fama-French 3 factor regression for the previous five-year estimation period. Dividend yield is the dividend payment of a firm in the previous fiscal year divided by its share price. Illiquid is the annual illiquidity measure (multiplied by 10.000) calculated following Amihud (2002).

Variables	Mean	StDev	P10	P25	Median	P75	P90
FIT	0.54	0.41	0.04	0.23	0.49	0.75	1.03
FIB	0.28	0.23	0.01	0.10	0.24	0.39	0.56
FIS	0.25	0.21	0.01	0.07	0.21	0.35	0.51
Institutional Ownership	0.37	0.27	0.01	0.13	0.35	0.57	0.74
Quarterly Turnover	0.22	0.23	0.04	0.08	0.15	0.27	0.46
Beta	0.82	0.56	0.15	0.41	0.77	1.15	1.55
Ln(ME)	20.03	1.58	18.14	18.81	19.85	21.02	22.18
BM	0.73	0.53	0.23	0.39	0.63	0.95	1.34
Ret(-6,-1)	0.10	0.33	-0.20	-0.06	0.07	0.21	0.42
Residual Analyst Coverage	-0.03	5.32	-5.33	-2.69	-0.52	2.45	6.33
Stock Price	40.23	883.24	9.13	13.63	21.75	34.00	50.25
Idiosyncratic Volatility	0.09	0.04	0.05	0.07	0.08	0.11	0.14
Dividend	0.03	0.09	0.00	0.00	0.02	0.05	0.08
Illiq	2.16	2.61	0.29	0.59	1.30	2.73	5.06

Table 2: Firm Characteristics Across FIT Levels

This table reports firms characteristics across FIT quintiles. Time-series means and t-statistics of the cross-sectional averages are reported. Betas of individual stocks are obtained from CRSP; Size is the natural log of a firm's market capitalization; BM/ME is calculated the summation of a firm's book equity and deferred tax divided by the firm's market equity; past return is the cumulative return of a firm during the past six months. The residual analyst coverage is calculated following Griffin and Lemmon (2002) by subtracting the average analyst coverage of the NYSE size quartile of a firm from the firm's analyst coverage. Turnover is the total quarterly turnover calculated as the summation of the monthly turnovers during the quarter, where monthly turnover is obtained by dividing the total trading volume of a firm by its total shares outstanding. Idiosyncratic volatility is the monthly updated volatility of residuals from a Fama-French 3 factor regression for the previous five-year estimation period. Dividend yield is the dividend payment of a firm in the previous fiscal year divided by its share price. Illiquid is the annual illiquidity measure calculated following Amihud (2002). Since Illiquidity levels vary over time with total market volumes, I transfer the illiquidity measures into standardized ranks between 0 and 1 following Chan, Jegadeesh, and Lakonishok (1996).

Variables	Low FIT	2	3	4	High FIT	High-Low	t-stat
FIB	0.03	0.16	0.26	0.36	0.56	0.53	94.92
FIS	0.03	0.14	0.24	0.33	0.51	0.48	82.18
Institutional Ownership	0.06	0.30	0.43	0.49	0.48	0.42	48.07
Quarterly Turnover	0.20	0.29	0.23	0.19	0.14	-0.06	-23.47
Beta	0.62	0.88	0.93	0.92	0.79	0.17	10.90
Ln(ME)	18.96	19.76	20.45	20.54	20.12	1.16	38.54
BM	0.73	0.75	0.74	0.73	0.75	0.01	1.30
Ret(-6,-1)	0.10	0.12	0.10	0.10	0.09	-0.01	-1.38
Residual Analyst Coverage	-1.62	0.34	1.25	0.75	-0.70	0.92	12.00
Stock Price	20.04	26.03	31.47	35.58	81.62	61.58	10.09
Idiosyncratic Volatility	0.09	0.10	0.09	0.09	0.09	0.00	-1.28
Dividend	0.05	0.03	0.03	0.03	0.03	-0.02	-13.88
SP500Dummy	0.02	0.15	0.31	0.33	0.19	0.18	16.41
Illiq	0.65	0.52	0.42	0.40	0.53	-0.19	-12.37

Table 3: Correlations

this table reports the correlation coefficients of the listed variables. FIT, FIB and FIS are measured in quarter t, and FIT_{t-1} is measured in quarter t-1. IO_{t-1}, institutional ownership, is measured at the end of quarter t-1. *Beta* is estimated using the daily returns in the previous calendar year. $Ln(ME)$ is the natural log of market capitalization measured at the end of quarter t-1. $Ln(BM)$ BE/ME is calculated according to Fama and French (1992). *Ret*6 is returns of the six-month period up to the end of quarter t-1. Prc is the stock price at the end of quarter t-1. $ResAC$ is the residual analyst coverage at the end of quarter t-1 calculated following Griffin and Lemmon (2002). $S\&P500$ is a dummy variable which equals 1 if at the beginning of quarter t the firm is part of S&P500 composite index. $Volty$ is firm level ideosyncratic volatility of CAPM estimated every year following a five-year rolling window process. Div is the dividend yield obtained by dividing a firm's dividend payment per share by its share price. *Illiq* is Amihud (2002)'s illiquidity measure estimated in the previous calendar year.

Models	FIT	FIB	FIS	FIT_{t-1}	IO_{t-1}	$Beta$	$Ln(ME)$	$Ln(BM)$	$Ret6$	Prc	$ResAC$	$SP500$	$Volty$	Div	$Illiq$
FIT	1.00														
FIB	0.84	1.00													
FIS	0.82	0.46	1.00												
FIT_{t-1}	0.68	0.59	0.62	1.00											
IO_{t-1}	0.48	0.41	0.50	0.49	1.00										
$Beta$	0.04	0.04	0.07	0.04	0.30	1.00									
$Ln(ME)$	0.23	0.21	0.25	0.24	0.46	0.25	1.00								
$Ln(BM)$	0.07	0.06	0.04	0.06	-0.02	-0.19	-0.15	1.00							
$Ret6$	-0.01	0.01	-0.03	-0.03	0.00	-0.02	0.03	0.06	1.00						
Prc	0.09	0.07	0.08	0.08	0.08	0.00	0.17	-0.02	0.04	1.00					
$ResAC$	0.00	0.01	0.02	0.00	0.28	0.16	0.13	-0.03	-0.09	-0.05	1.00				
$SP500$	0.12	0.11	0.13	0.12	0.40	0.19	0.65	-0.03	-0.03	0.08	0.26	1.00			
$Volty$	-0.09	-0.07	-0.08	-0.10	0.00	0.35	-0.22	-0.15	0.13	-0.07	0.09	-0.15	1.00		
Div	-0.12	-0.12	-0.12	-0.12	-0.21	-0.30	-0.04	0.20	-0.01	-0.02	-0.09	-0.01	-0.35	1.00	
$Illiq$	-0.08	-0.07	-0.12	-0.09	-0.48	-0.30	-0.86	0.15	0.11	-0.12	-0.20	-0.61	0.20	0.00	1.00

Table 4: Quarterly Fama-Macbeth Regressions: Determinants of Trader Composition

This table presents quarterly Fama-Macbeth regressions of FIT (M1-M4), FIB (M5-M6) and FIS (M7-M8). FIT_{t-1}, FIB_{t-1}, and FIS_{t-1} are one quarter lags. IO_{t-1} is institutional ownership at the end of quarter t-1. $Beta$ is estimated using the daily returns in the previous calendar year. $Ln(ME)_{t-1}$ is the natural log of market capitalization at the end of quarter t-1. $Ln(BM)$ is BE/ME. $Ret6$ is six-month return up quarter t-1. Prc_{t-1} is stock price at the end of quarter t-1. $ResAC$ is residual analyst coverage at the end of quarter t-1. $S\&P500$ is a dummy variable which equals 1 if the firm is part of S&P500 composite index. $Volatility$ is CAPM ideosyncratic volatility. $Dividend$ is dividend yield. $illiq$ is Amihud (2002)'s illiquidity measure. Average Adj. R-square is the time series averages. In order to facilitate the estimation of economic significance, I follow Chan, Jegadeesh and Lakonishok (1996) to transform the independent variables into standardized ranks between 0 and 1. t-statistics are calculated based on Newey-West standard errors.

	FIT Regressions				FIB Regressions		FIS Regressions	
Models	M1	M2	M3	M4	M5	M6	M7	M8
FIT_{t-1}	0.9337	0.7627		0.8879				
t-stat	(31.13)	(23.94)		(16.56)				
FIB_{t-1}					0.2612	0.2863	0.2364	0.2670
t-stat					(34.35)	(27.12)	(22.88)	(15.96)
FIS_{t-1}					0.2120	0.2429	0.1646	0.1979
t-stat					(17.44)	(13.90)	(22.55)	(15.87)
IO_{t-1}		0.2323	0.6742	0.2341	0.0406	0.0416	0.1557	0.1570
t-stat		(7.00)	(23.07)	(7.16)	(3.11)	(3.30)	(8.03)	(8.30)
$Beta$		-0.0547	-0.1000	-0.0561	-0.0215	-0.0222	-0.0243	-0.0251
t-stat		(-8.41)	(-8.29)	(-8.54)	(-6.62)	(-6.79)	(-8.23)	(-8.55)
$Ln(ME)_{t-1}$		0.0261	0.1016	0.0235	0.0012	0.0008	0.0181	0.0173
t-stat		(1.70)	(4.80)	(1.66)	(0.14)	(0.09)	(4.20)	(4.37)
$Ln(BM)$		0.0240	0.0497	0.0238	0.0156	0.0157	0.0013	0.0012
t-stat		(2.83)	(2.87)	(2.76)	(3.69)	(3.64)	(0.27)	(0.26)
$Ret6$		-0.0188	-0.0716	-0.0188	0.0089	0.0087	-0.0274	-0.0277
t-stat		(-2.87)	(-6.58)	(-2.90)	(1.87)	(1.81)	(-8.05)	(-8.42)
Prc_{t-1}		-0.0271	-0.1033	-0.0268	-0.0045	-0.0045	-0.0182	-0.0185
t-stat		(-1.16)	(-2.16)	(-1.14)	(-0.37)	(-0.37)	(-2.02)	(-2.02)
$ResAC$		-0.0772	-0.1480	0.0628	-0.0265	0.0368	-0.0404	0.0314
t-stat		(-18.63)	(-13.12)	(1.96)	(-9.18)	(2.27)	(-19.39)	(1.61)
$S\&P500$		-0.0783	-0.1577	-0.0769	-0.0293	-0.0293	-0.0393	-0.0394
t-stat		(-12.62)	(-9.78)	(-12.37)	(-11.60)	(-11.70)	(-11.51)	(-11.54)
$Volatility$		-0.1046	-0.2569	-0.1003	-0.0545	-0.0528	-0.0409	-0.0392
t-stat		(-15.30)	(-12.81)	(-14.73)	(-13.34)	(-12.52)	(-11.69)	(-11.51)
$Dividend$		-0.0731	-0.1423	-0.0737	-0.0468	-0.0474	-0.0148	-0.0153
t-stat		(-8.20)	(-7.52)	(-7.60)	(-8.59)	(-8.18)	(-4.92)	(-4.44)
$Illiq$		0.1381	0.2625	0.1360	0.0566	0.0557	0.0578	0.0568
t-stat		(10.42)	(8.88)	(10.86)	(9.16)	(9.44)	(8.10)	(8.36)
$ResAC * FIT$				-0.2424				
t-stat				(-4.12)				
$ResAC * FIB$						-0.0486		-0.0598
t-stat						(-2.46)		(-2.83)
$ResAC * FIS$						-0.0606		-0.0641
t-stat						(-3.84)		(-3.98)
Adj. R-sq	0.4180	0.4583	0.2369	0.4688	0.3614	0.3646	0.4030	0.4071

Table 5: Persistence in Trader Composition: Sub-Portfolio Analysis

Panel A reports the average FIT across lag FIT deciles. Panel B reports the average FIS across lag FIB deciles, and Panel C reports the average FIS across lag FIS deciles. Each quarter, I sort stocks into deciles according to their one quarter lag FIT (Panel A), or lag FIB (Panel B), or lag FIS (Panel C), and calculate average FIT, or FIB, or FIS for each decile. I then calculate the time series means and t-statistics of the cross-sectional averages for each.

	Low 1	2	3	4	5	6	7	8	9	High 10	High-Low	t-value
Panel A: FIT Across Deciles of One Quarter Lag FIT												
FIT (%)	0.08	0.17	0.32	0.43	0.52	0.60	0.67	0.75	0.84	1.02	0.94	(77.07)
LagFIT(%)	0.02	0.09	0.23	0.35	0.45	0.55	0.64	0.75	0.90	1.40	1.38	
Panel B: FIB Across Deciles of One Quarter Lag FIB												
FIB (%)	0.06	0.09	0.17	0.23	0.27	0.31	0.34	0.38	0.42	0.47	0.41	(66.26)
LagFIB(%)	0.00	0.04	0.10	0.16	0.22	0.27	0.33	0.40	0.49	0.76	0.75	
Panel C: FIS Across Deciles of One Quarter Lag FIS												
FIS (%)	0.06	0.08	0.15	0.21	0.24	0.28	0.31	0.35	0.37	0.42	0.36	(63.47)
LagFIS(%)	0.00	0.02	0.07	0.14	0.19	0.24	0.30	0.36	0.44	0.70	0.70	

Table 6: Stock Returns and Trader Composition: Sub-Portfolio Analysis

This table reports the average monthly stock returns of lag FIT (Panel A), and lag residual FIT (Panel B) deciles. Each month, I sort stocks into deciles of FIT, or residual FIT (ResFIT) of the previous quarter and calculate average monthly stock returns for each decile portfolio. I then report the time series means and t-statistics of the cross-sectional return averages. Jensen alphas, and Carhart 4-factor alphas are calculated using CAPM, and Carhart (1997) four factor model. I also report DGTW returns for the FIT deciles, where the DGTW benchmark returns are obtained from Russ Wermers' data library. All the t-statistics are calculated with Newey-West robust standard errors.

Panel A: Fraction of Institutional Trading Volume (FIT)												
	Low FIT	2	3	4	5	6	7	8	9	High FIT	High-Low	t-stat
Raw Returns	0.96	1.23	1.17	1.27	1.29	1.43	1.35	1.36	1.40	1.45	0.49	(3.29)
Jensen Alpha	-0.11	0.14	0.09	0.22	0.24	0.36	0.32	0.32	0.36	0.46	0.57	(3.09)
Carhart Alpha	-0.21	0.03	-0.13	-0.02	-0.01	0.09	0.02	0.01	0.06	0.11	0.32	(1.98)
DGTW Adj. Returns	-0.16	0.05	-0.13	-0.12	0.12	0.13	0.04	0.09	0.10	0.13	0.29	(2.41)
Panel B: Residual Fraction of Institutional Trading Volume (ResFIT)												
	Low ResFIT	2	3	4	5	6	7	8	9	High ResFIT	High-Low	t-stat
Raw Returns	1.20	1.07	0.97	1.12	1.19	1.29	1.30	1.40	1.44	1.39	0.20	(1.37)
Jensen Alpha	0.00	0.05	0.00	0.10	0.17	0.27	0.29	0.39	0.43	0.42	0.42	(3.58)
Carhart Alpha	-0.11	-0.10	-0.16	-0.13	-0.12	0.02	-0.01	0.08	0.09	0.11	0.22	(2.13)
DGTW Adj. Returns	-0.10	-0.08	-0.05	-0.13	0.05	0.06	-0.01	0.12	0.14	0.11	0.21	(2.11)

Table 7: Stock Returns of Portfolios Double Sorted on FIT and Illiquidity

This table reports the average monthly stock returns of portfolios two-dimensionally sorted on lag FIT and stock illiquidity. Each month, I sort stocks into deciles of lag of the previous quarter and calculate average monthly stock returns for each two-dimensional portfolios. The stock illiquidity measure is calculated following Amihud (2002). I then report the time series means and t-statistics of the cross-sectional return averages. All the t-statistics are calculated with Newey-West robust standard errors.

	Low FIT	2	3	4	High FIT	High-Low	t-stat
Liquid	0.67	0.93	1.19	1.24	1.36	0.69	(2.63)
2	0.65	1.04	1.25	1.36	1.47	0.82	(4.85)
3	0.72	0.96	1.30	1.39	1.36	0.64	(3.91)
4	0.97	1.28	1.58	1.39	1.47	0.49	(3.11)
Illiquid	1.17	1.67	1.59	1.60	1.44	0.28	(2.06)
Liquid-Illiquid						0.41	(1.74)

Table 8: Momentum and Trader Composition: Sub-Portfolio Analysis

I apply 6-month formation/6-month holding momentum strategy and examine momentum profits across terciles of FIT (Panel A), and Residual FIT (Panel B). In particular, at the beginning of each month, an independent sort is used to rank stocks into deciles of their past six-month returns and three groups of one quarter lag FIT (Panel A), or residual FIT (Panel B). The ranked stocks are assigned to one of 30 two dimensionally sorted portfolios which are held for six months. In order to avoid the microstructure effect, there is an one-month interval between the portfolio formation date and the six-month return measurement period as in Jegadeesh and Titman (1993). The t-statistics are calculated with Newey-West robust standard errors.

	Loser	2	3	4	5	6	7	8	9	Winner	Winner - Loser	t-stat
Panel A: Fraction of Institutional Trading Volume (FIT)												
Low FIT	0.23	0.72	0.94	1.00	1.07	1.13	1.15	1.19	1.40	1.70	1.48	(6.24)
Med. FIT	0.64	1.05	1.13	1.26	1.27	1.32	1.30	1.35	1.42	1.69	1.05	(4.72)
High FIT	0.81	1.14	1.23	1.32	1.35	1.31	1.36	1.38	1.46	1.76	0.95	(4.46)
Low - High											0.53	(3.40)
Panel B: Residual Fraction of Institutional Trading Volume (ResFIT)												
Low ResFIT	0.35	0.81	0.96	1.07	1.09	1.16	1.16	1.18	1.39	1.72	1.37	(5.64)
Med. ResFIT	0.49	0.98	1.07	1.18	1.18	1.20	1.25	1.30	1.40	1.66	1.17	(5.44)
High ResFIT	0.82	1.15	1.27	1.33	1.38	1.36	1.40	1.42	1.48	1.72	0.90	(4.35)
Low - High											0.47	(3.44)

Table 9: Quarterly Fama-Macbeth Regressions: Momentum and Trader Composition

This table reports quarterly Fama-Macbeth regressions of stock returns (constants not reported). The independent variable is quarterly cumulative stock returns (%). The independent variables are measured at the end of the previous quarter. Each quarter I run a cross sectional regression and then calculate time series means and t-stats of the coefficients. FIT, FIB and FIS are calculated following equations (1) to (6) in the paper. Betas are obtained from CRSP; ME is a firm's market capitalization; BM is the book-to-market ratio. Ret(-6,-1) is the cumulative return of a firm during the past six months. IO is the institutional ownership. ResAC is the residual analyst coverage. Turnover is the total quarterly turnover. I follow Chan, Jegadeesh and Lakonishok (1996) to transform the independent variables into standardized ranks between 0 and 1. There is one-month interval before the return measurement period. The t-statistics are calculated based on Newey-West standard errors.

Models	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Ret(-6,-1)	4.61	3.77	4.84	6.25	4.99	5.09	6.18
t-stat	(5.80)	(5.00)	(5.62)	(6.23)	(5.71)	(5.64)	(6.05)
Beta	-0.57	-0.82	-0.65	-0.48	-0.60	-0.67	-0.51
t-stat	(-0.63)	(-0.93)	(-0.76)	(-0.62)	(-0.66)	(-0.78)	(-0.65)
Ln(ME)(t-1)	-0.85	-0.90	-0.97	1.41	-0.95	-1.04	1.27
t-stat	(-1.12)	(-1.09)	(-1.18)	(1.60)	(-1.24)	(-1.27)	(1.46)
BE/ME	1.46	1.46	1.43	1.95	1.44	1.42	1.96
t-stat	(3.10)	(3.09)	(3.08)	(3.67)	(3.07)	(3.07)	(3.69)
Turnover(t-1)				-1.64			-1.75
t-stat				(-2.43)			(-2.63)
Res-AnalystCoverage(t-1)				0.92			0.87
t-stat				(1.67)			(1.59)
FIT(t-1)	3.52		3.09	2.39			
t-stat	(5.02)		(5.25)	(4.20)			
FIB(t-1)					1.82	1.61	1.00
t-stat					(2.96)	(2.81)	(1.82)
FIS(t-1)					2.36	2.20	1.80
t-stat					(3.99)	(3.88)	(3.24)
IO(t-1)		2.54	0.91	0.66		0.64	0.58
t-stat		(3.03)	(1.16)	(0.92)		(0.83)	(0.84)
FIT(t-1)*Ret(-6,-1)	-4.21		-3.88	-2.78			
t-stat	(-4.08)		(-3.91)	(-3.02)			
FIB(t-1)*Ret(-6,-1)					-1.98	-1.88	-0.94
t-stat					(-2.07)	(-1.96)	(-1.01)
FIS(t-1)*Ret(-6,-1)					-2.87	-2.81	-2.05
t-stat					(-2.98)	(-2.86)	(-2.26)
IO(t-1)*Ret(-6,-1)		-2.57	-0.69	0.10		-0.29	0.09
t-stat		(-2.45)	(-0.66)	(0.09)		(-0.27)	(0.08)
Ln(ME)(t-1)*Ret(-6,-1)				-4.82			-4.70
t-stat				(-4.91)			(-4.86)
BM*Ret(-6,-1)				-1.06			-1.10
t-stat				(-1.68)			(-1.65)
Turnover(t-1)*Ret(-6,-1)				2.17			2.40
t-stat				(2.23)			(2.48)
ResAC(t-1)*Ret(-6,-1)				-1.07			-0.98
t-stat				(-1.25)			(-1.16)
Average Adj. R-square	0.0520	0.0534	0.0603	0.0641	0.0543	0.0567	0.0650

Table 10: PEAD and Trader Composition: Sub-Portfolio Analysis

This table examines the relationship between PEAD and FIT/ResFIT. For this test I apply a rolling strategy based on earnings-announcement shock proposed by Frazzini (2005). In particular, at the beginning of each month, an independent sort is used to rank stocks into ten groups of their most recent quarterly earnings-announcement shock and three groups of one quarter lag FIT (Panel A), or lag residual FIT (Panel B). The ranked stocks are assigned to one of the 30 two dimensionally sorted portfolios, and then each of these portfolios are held for six months. There is a one-month interval between portfolio formation and return measurement period in order to control for microstructure effect. Quarterly earnings-announcement shocks are measured using the market model abnormal returns from two days prior to the quarterly announcement date to one day after the announcement date. The t-statistics are calculated with Newey-West robust standard errors.

	LowES	2	3	4	5	6	7	8	9	HighES	HighES- LowES	t-stat
Panel A: Fraction of Institutional Trading Volume (FIT)												
Low FIT	0.66	1.00	1.09	1.12	1.09	1.24	1.23	1.28	1.32	1.48	0.82	(8.69)
Med. FIT	1.06	1.22	1.24	1.32	1.28	1.35	1.33	1.34	1.34	1.30	0.24	(2.73)
High FIT	1.12	1.26	1.27	1.31	1.32	1.36	1.37	1.41	1.50	1.43	0.32	(3.46)
Low - High											0.50	(4.19)
Panel B: Residual Fraction of Institutional Trading Volume (ResFIT)												
Low ResFIT	0.79	1.03	1.12	1.10	1.13	1.26	1.27	1.27	1.30	1.43	0.64	(7.92)
Med. ResFIT	0.87	1.21	1.21	1.26	1.19	1.33	1.26	1.34	1.35	1.28	0.41	(4.48)
High ResFIT	1.12	1.24	1.26	1.37	1.37	1.37	1.42	1.44	1.51	1.51	0.39	(4.37)
Low - High											0.26	(2.73)

Table 11: Quarterly Fama-Macbeth Regressions: PEAD and Trader Composition

This table reports quarterly Fama-Macbeth regressions of stock returns (constants not reported). The independent variable is quarterly cumulative stock returns (%). The independent variables are measured at the end of the previous quarter. Each quarter I run a cross sectional regression and then calculate time series means and t-stats of the coefficients. EarningsShock is the earnings-announcement shock measured using the market model abnormal returns from two days prior to the quarterly announcement date to one day after the announcement date. FIT, FIB, and FIS are calculated following equations (1) to (6) in the paper. Betas are obtained from CRSP; ME is a firm's market capitalization; BM is the book-to-market ratio. Ret(-6,-1) is the cumulative return of a firm during the past six months. IO is the institutional ownership. I follow Chan, Jegadeesh and Lakonishok (1996) to transform the independent variables into standardized ranks between 0 and 1. To facilitate the evaluation of economic significance, I follow Chan, Jegadeesh, and Lakonishok (1996) to transform the independent variables into standardized ranks between 0 and 1. To control for the microstructure effect, there is one-month interval before the return measurement period. The t-statistics are calculated based on Newey-West standard errors.

Models	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
EarningsShock	1.95	1.90	2.42	3.15	2.23	2.55	3.26
t-stat	(4.28)	(4.30)	(4.68)	(5.47)	(4.28)	(4.78)	(5.49)
Beta	-0.64	-0.85	-0.71	-0.70	-0.66	-0.72	-0.70
t-stat	(-0.74)	(-1.00)	(-0.87)	(-0.85)	(-0.75)	(-0.86)	(-0.84)
Ln(ME)(t-1)	-0.97	-1.01	-1.10	0.42	-1.09	-1.19	0.34
t-stat	(-1.24)	(-1.18)	(-1.30)	(0.46)	(-1.37)	(-1.38)	(0.37)
BE/ME	1.34	1.36	1.33	1.33	1.32	1.31	1.31
t-stat	(2.75)	(2.77)	(2.75)	(2.76)	(2.72)	(2.76)	(2.76)
Ret(-6,-1)	2.20	2.16	2.21	2.20	2.22	2.24	2.23
t-stat	(3.52)	(3.45)	(3.56)	(3.53)	(3.53)	(3.49)	(3.46)
FIT(t-1)	2.54		1.94	1.80			
t-stat	(4.33)		(3.74)	(3.42)			
FIB(t-1)					1.59	1.19	0.97
t-stat					(2.65)	(2.13)	(1.73)
FIS(t-1)					1.51	1.26	1.28
t-stat					(3.37)	(2.65)	(2.72)
IO(t-1)		2.22	1.29	0.71		1.11	0.57
t-stat		(3.32)	(2.05)	(1.19)		(1.80)	(0.98)
FIT(t-1)*EarningsShock	-2.63		-1.80	-1.54			
t-stat	(-3.80)		(-2.43)	(-1.99)			
FIB(t-1)*EarningsShock					-1.42	-0.79	-0.41
t-stat					(-1.54)	(-0.88)	(-0.46)
FIS(t-1)*EarningsShock					-1.73	-1.44	-1.45
t-stat					(-2.34)	(-1.89)	(-1.95)
IO(t-1)*EarningsShock		-2.40	-1.66	-0.50		-1.47	-0.37
t-stat		(-3.44)	(-2.17)	(-0.70)		(-1.92)	(-0.52)
Ln(ME)(t-1)*EarningsShock				-3.07			-3.07
t-stat				(-4.17)			(-4.13)
Average Adj. R-square	0.0535	0.0545	0.0562	0.0568	0.0548	0.0571	0.0576

Table 12: Value Premium and Trader Composition: Sub-Portfolio Analysis

This table examines the relationship between the value premium and trader composition. In particular, at the beginning of each month, an independent sort is used to rank stocks on ten groups of their book-to-market ratios and three groups of one quarter lag FIT (Panel A), or lag residual FIT (Panel B). The ranked stocks are assigned to one of the 30 two-dimensionally sorted portfolios, and I then examine the time-series means and t-statistics of the monthly returns of these portfolios. The t-statistics are calculated with Newey-West robust standard errors.

	Low BM	2	3	4	5	6	7	8	9	High BM	HighBM - LowBM	t-stat
Panel A: Fraction of Institutional Trading Volume (FIT)												
Low FIT	0.58	0.89	1.08	1.17	1.38	1.08	1.26	1.30	1.32	1.48	0.90	(3.37)
Med. FIT	1.04	1.15	1.26	1.28	1.41	1.26	1.43	1.38	1.47	1.72	0.68	(2.95)
High FIT	1.28	1.31	1.34	1.40	1.35	1.40	1.39	1.46	1.48	1.55	0.27	(1.41)
Low - High											0.63	(2.85)
Panel B: Residual Fraction of Institutional Trading Volume (ResFIT)												
Low ResFIT	0.72	0.94	1.14	1.10	1.36	1.16	1.23	1.32	1.34	1.45	0.73	(3.07)
Med. ResFIT	0.78	1.03	1.26	1.39	1.35	1.35	1.33	1.33	1.36	1.65	0.87	(3.53)
High ResFIT	1.30	1.40	1.33	1.37	1.43	1.27	1.47	1.48	1.58	1.62	0.32	(1.51)
Low - High											0.41	(2.19)

Table 13: Monthly Fama-Macbeth Regressions: Value premium and Trader Composition

This table reports monthly Fama-Macbeth regressions of stock returns (constants not reported). The independent variable is monthly stock returns (%). The independent variables are measured at the end of the previous month. Each month I run a cross sectional regression and then calculate time series means and t-stats of the coefficients. FIT, FIB, and FIS are calculated following equations (1) to (6) in the paper. Betas are obtained from CRSP; ME is a firm's market capitalization; BM is the book-to-market ratio. Ret(-6,-1) is the cumulative return of a firm during the past six months skipping a month. IO is the institutional ownership at the beginning of the quarter. To facilitate the evaluation economic significance, I follow Chan, Jegadeesh, and Lakonishok (1996) to transform the independent variables into standardized ranks between 0 and 1. The t-statistics are calculated based on Newey-West standard errors.

Models	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
BE/ME	0.84	0.83	0.93	0.89	0.83	0.89	0.86
t-stat	(3.63)	(3.74)	(3.82)	(3.45)	(3.68)	(3.82)	(3.50)
Beta	-0.10	-0.19	-0.13	-0.13	-0.12	-0.14	-0.14
t-stat	(-0.35)	(-0.63)	(-0.44)	(-0.42)	(-0.41)	(-0.49)	(-0.48)
Ln(ME)(t-1)	-0.37	-0.38	-0.42	-0.46	-0.39	-0.43	-0.45
t-stat	(-1.45)	(-1.39)	(-1.53)	(-1.40)	(-1.52)	(-1.60)	(-1.41)
Ret(-6,-1)	0.68	0.67	0.68	0.68	0.73	0.74	0.74
t-stat	(3.11)	(3.06)	(3.16)	(3.16)	(3.24)	(3.32)	(3.32)
FIT(t-1)	0.92		0.71	0.70			
t-stat	(3.92)		(2.99)	(2.94)			
FIB(t-1)					0.31	0.20	0.18
t-stat					(1.70)	(1.09)	(0.98)
FIS(t-1)					0.70	0.60	0.61
t-stat					(3.80)	(3.24)	(3.31)
IO(t-1)		0.79	0.38	0.40		0.33	0.33
t-stat		(3.52)	(1.70)	(1.65)		(1.58)	(1.46)
FIT(t-1)*BM	-0.79		-0.56	-0.54			
t-stat	(-3.02)		(-1.89)	(-1.84)			
FIB(t-1)*BM					-0.29	-0.17	-0.14
t-stat					(-1.20)	(-0.69)	(-0.57)
FIS(t-1)*BM					-0.56	-0.45	-0.45
t-stat					(-2.21)	(-1.69)	(-1.71)
IO(t-1)*BM		-0.73	-0.40	-0.43		-0.36	-0.36
t-stat		(-2.67)	(-1.29)	(-1.29)		(-1.21)	(-1.15)
Ln(ME)(t-1)*BM				0.09			0.04
t-stat				(0.31)			(0.15)
Average Adj. R-square	0.0479	0.0480	0.0512	0.0520	0.0495	0.0526	0.0533

Table 14: Momentum and Trader Composition: Sub-Period Analysis

I apply 6-month formation/6-month holding momentum strategy and examine momentum profits across terciles of FIT during the three sub-periods of 1980-1987 (Panel A), 1988-1996 (Panel B) and 1997-2005 (Panel C). In particular, at the beginning of each month, an independent sort is used to rank stocks into deciles of their past six-month returns and three groups of one quarter lag FIT. The ranked stocks are assigned to one of 30 two dimensionally sorted portfolios which are held for six months. In order to avoid the microstructure effect, there is an one-month interval between the portfolio formation date and the six-month return measurement period as in Jegadeesh and Titman (1993). The t-statistics are calculated with Newey-West robust standard errors.

	Loser	2	3	4	5	6	7	8	9	Winner	Winner - Loser	t-stat
Panel A: Sub-Sample Analysis: 1980-1987												
Low FIT	0.09	0.95	1.31	1.28	1.35	1.47	1.29	1.36	1.51	1.48	1.38	(4.21)
Med. FIT	0.60	1.21	1.33	1.46	1.50	1.53	1.51	1.53	1.39	1.49	0.89	(2.49)
High FIT	0.80	1.24	1.37	1.53	1.59	1.62	1.56	1.53	1.53	1.67	0.87	(2.09)
Low - High											0.51	(1.80)
Panel B: Sub-Sample Analysis: 1988-1996												
Low FIT	0.31	0.80	0.93	1.00	0.99	1.05	1.25	1.21	1.41	1.83	1.51	(4.65)
Med. FIT	0.75	1.10	1.23	1.37	1.38	1.42	1.37	1.43	1.54	1.88	1.12	(3.37)
High FIT	0.83	1.14	1.24	1.34	1.32	1.26	1.33	1.35	1.44	1.81	0.98	(3.21)
Low - High											0.53	(2.59)
Panel C: Sub-Sample Analysis: 1997-2005												
Low FIT	0.24	0.46	0.64	0.79	0.94	0.95	0.95	1.02	1.31	1.76	1.51	(2.96)
Med. FIT	0.56	0.88	0.87	0.99	0.96	1.05	1.06	1.14	1.31	1.66	1.10	(2.50)
High FIT	0.80	1.07	1.10	1.15	1.19	1.11	1.25	1.30	1.44	1.77	0.97	(2.52)
Low - High											0.54	(2.73)

Table 15: PEAD and Trader Composition: Sub-Period Analysis

This table examines the relationship between PEAD and FIT during the three sub-periods of 1980-1987 (Panel A), 1988-1996 (Panel B) and 1997-2005 (Panel C).. For this test I apply a rolling strategy based on earnings-announcement shock proposed by Frazzini (2005). In particular, at the beginning of each month, an independent sort is used to rank stocks into ten groups of their most recent quarterly earnings-announcement shock and three groups of one quarter lag FIT. The ranked stocks are assigned to one of the 30 two dimensionally sorted portfolios, and then each of these portfolios are held for six months. There is a one-month interval between portfolio formation and return measurement period in order to control for microstructure effect. Quarterly earnings-announcement shocks are measured using the market model abnormal returns from two days prior to the quarterly announcement date to one day after the announcement date. The t-statistics are calculated with Newey-West robust standard errors.

	LowES	2	3	4	5	6	7	8	9	HighES	HighES- LowES	t-stat
Panel A: Sub-Sample Analysis: 1980-1987												
Low FIT	0.30	0.99	1.17	1.35	1.23	1.50	1.37	1.41	1.39	1.31	1.00	(6.66)
Med. FIT	0.79	1.20	1.25	1.58	1.44	1.63	1.47	1.45	1.50	1.39	0.60	(4.67)
High FIT	1.15	1.27	1.35	1.51	1.51	1.54	1.58	1.57	1.72	1.62	0.47	(3.01)
Low - High											0.54	(3.11)
Panel B: Sub-Sample Analysis: 1988-1996												
Low FIT	0.99	1.26	1.16	1.06	1.12	1.15	1.25	1.29	1.36	1.73	0.74	(4.70)
Med. FIT	1.34	1.33	1.35	1.41	1.33	1.39	1.31	1.34	1.42	1.45	0.11	(0.81)
High FIT	1.11	1.38	1.26	1.24	1.27	1.35	1.32	1.40	1.42	1.42	0.31	(1.97)
Low - High											0.43	(2.04)
Panel C: Sub-Sample Analysis: 1997-2005												
Low FIT	0.60	0.73	0.96	0.98	0.95	1.13	1.11	1.16	1.22	1.35	0.75	(4.14)
Med. FIT	0.99	1.13	1.11	1.01	1.08	1.08	1.23	1.24	1.11	1.05	0.07	(0.40)
High FIT	1.09	1.10	1.22	1.22	1.21	1.23	1.26	1.28	1.40	1.29	0.20	(1.20)
Low - High											0.55	(2.46)

Table 16: Value Premium and Trader Composition: Sub-Period Analysis

This table examines the relationship between the value premium and FIT during the three sub-periods of 1980-1987 (Panel A), 1988-1996 (Panel B) and 1997-2005 (Panel C).. In particular, at the beginning of each month, an independent sort is used to rank stocks on ten groups of their book-to-market ratios and three groups of one quarter lag FIT. The ranked stocks are assigned to one of the 30 two-dimensionally sorted portfolios, and I then examine the time-series means and t-statistics of the monthly returns of these portfolios. The t-statistics are calculated with Newey-West robust standard errors.

	Low BM	2	3	4	5	6	7	8	9	High BM	HighBM - LowBM	t-stat
Panel A: Sub-Sample Analysis: 1980-1987												
Low FIT	0.13	0.73	0.85	1.33	1.67	1.39	1.65	1.41	1.48	1.70	1.58	(2.82)
Med. FIT	0.99	1.27	1.31	1.61	1.77	1.33	1.87	1.44	1.88	2.10	1.11	(2.83)
High FIT	1.37	1.36	1.54	1.66	1.54	1.66	1.82	1.57	1.60	1.74	0.38	(1.11)
Low - High											1.20	(3.20)
Panel B: Sub-Sample Analysis: 1988-1996												
Low FIT	0.96	1.21	1.39	1.22	1.38	0.96	1.09	1.41	1.04	1.32	0.36	(1.22)
Med. FIT	1.31	1.14	1.25	1.28	1.34	1.37	1.36	1.39	1.39	1.57	0.26	(0.65)
High FIT	1.20	1.24	1.41	1.38	1.45	1.28	1.34	1.60	1.44	1.48	0.28	(1.04)
Low - High											0.08	(0.27)
Panel C: Sub-Sample Analysis: 1997-2005												
Low FIT	0.58	0.68	0.95	0.97	1.13	0.94	1.10	1.09	1.46	1.45	0.88	(1.81)
Med. FIT	0.81	1.05	1.23	1.02	1.19	1.09	1.15	1.33	1.21	1.55	0.75	(1.99)
High FIT	1.28	1.34	1.09	1.21	1.08	1.30	1.10	1.22	1.43	1.45	0.17	(0.45)
Low - High											0.70	(1.69)

Table 17: Calculation of PPIndex

In each cross-section, I put stocks into ten portfolios according to their cumulative returns during the past six months. The portfolios are sorted in ascending order from extreme past losers to extreme past winners. Then I assign discrete PPIndex from -5 to 5 to the past-return portfolios, where -5 is assigned to the bottom past-return decile and 5 assigned to the top past-return decile.

Return Portfolios	Loser	2	3	4	5	6	7	8	9	Winner
Ppindex	-5	-4	-3	-2	-1	1	2	3	4	5

Table 18: Summary Statistics of the MT Measure

I calculate the MT measure for each firm-quarter during the 1982-2005 on a two-year rolling basis following equation (1). In particular, for each individual stock I calculate the MT measures during two-year estimation periods and apply them to the subsequent quarters. This table reports for the first quarter of every three-year period the number of firms as well as mean, standard deviation, t-statistic, median, 10% cutoff, 1/4 quartile, 3/4 quartile and 90% cutoff of the MT measures. I also report these statistics for the whole sample period. There are in total 367,337 firm-quarter observations with available MT measure.

Quarter	Obs	Mean	Std.	t-stat	10P	25P	Median	75P	90P
Total	367,337	0.31	2.31	81.88	-2.62	-1.27	0.25	1.87	3.52
1st Quarter, 1982	2,552	0.39	2.24	8.91	-2.35	-1.14	0.35	1.98	3.45
1st Quarter, 1985	2,786	0.38	2.20	9.13	-2.37	-1.09	0.37	1.82	3.24
1st Quarter, 1988	3,088	0.23	2.25	5.63	-2.57	-1.27	0.17	1.62	3.33
1st Quarter, 1991	3,145	0.33	2.30	8.16	-2.64	-1.22	0.36	1.88	3.43
1st Quarter, 1994	3,720	0.38	2.33	9.99	-2.62	-1.23	0.27	1.98	3.81
1st Quarter, 1997	4,731	0.37	2.37	10.72	-2.54	-1.29	0.14	2.00	4.00
1st Quarter, 2000	4,999	0.31	2.24	9.64	-2.53	-1.19	0.25	1.76	3.35
1st Quarter, 2003	4,499	0.15	2.42	4.06	-3.14	-1.56	0.19	1.82	3.36

Table 19: The MT Measure and Firm Characteristics

This table describes the relationships between the MT measures and firm characteristics. In particular, for each month of the sample period, I sort stocks into quintiles according to the MT measures of month t and calculate average return, size, book-to-market ratio, demeaned turnover, coverage, and MT measures of each quintile. The time series means and t-statistics of the firm characteristics are reported. Return is stock return of month t. Size is the natural log of market capitalization at the end of month t-1. BE/ME is the book-to-market ratio of month t. Turnover is demeaned turnover of month t-1. Coverage is the residual analyst coverage of month t-1 calculated following Griffin and Lemmon (2002). RetVolty is return volatility, measured as standard deviation of daily stock returns in the 25 trading days up to the end of month t-1. FirmAge is age of a firm measured as the number of months from the firm's first CRSP monthly return record.

MT Level	Low	2	3	4	High	High-Low	t-stat
Return	1.01	1.21	1.25	1.17	1.17	0.16	0.87
Size	19.96	20.24	20.30	20.20	19.78	-0.18	-15.25
BM	0.69	0.68	0.66	0.63	0.57	-0.12	-18.49
Turnover	0.01	0.00	0.00	0.01	0.05	0.04	17.70
Coverage	0.64	0.36	0.32	0.14	-0.15	-0.79	-17.56
RetVolty	0.024	0.020	0.021	0.022	0.028	0.004	13.21
FirmAge	196	232	231	206	143	-53	-40.43
MT	-2.47	-0.84	0.23	1.35	3.28	5.74	

Table 20: Return Momentum Across MT Groups: 1982-2005

I sort stocks independently into three groups of MT and ten groups of past performance, and calculate profits of six-month formation/six-month holding strategy following Jegadeesh and Titman (2001) for each MT group. Specifically, at the beginning of month t, I sort stocks into three groups of the MT measures and deciles of cumulative stock returns during the six-month period up to the end of month t-1. I then hold these portfolios for six months from the beginning of month t and report average portfolio returns in Panel A. Panel B reports the results of Fama-French three-factor model of the momentum profits of the low, medium and high MT terciles. The t-statistics are calculated with Newey-West robust standard errors.

Panel A: Momentum Profits Across MT Terciles

MT Level	Loser	2	3	4	5	6	7	8	9	Winner	Winner - Loser	t-stat
Low	0.61	0.99	1.20	1.21	1.22	1.20	1.25	1.28	1.37	1.69	1.08	(2.95)
Medium	0.62	1.05	1.23	1.27	1.33	1.35	1.36	1.43	1.54	1.83	1.21	(3.48)
High	0.22	0.94	1.00	1.19	1.19	1.25	1.30	1.33	1.48	1.83	1.61	(4.72)
High - Low											0.53	(3.21)

Panel B: Fama-French 3 Factor Regressions of Momentum Profits

MT Level	Intercept	MKT	SMB	HML
Low	1.32	-0.33	0.31	-0.08
	(3.52)	(-3.05)	(1.34)	(-0.30)
Medium	1.43	-0.29	0.28	-0.08
	(3.82)	(-2.62)	(1.21)	(-0.34)
High	1.80	-0.20	0.26	-0.17
	(4.84)	(-2.02)	(1.24)	(-0.76)
High - Low	0.48	0.13	-0.05	-0.09
	(3.02)	(3.19)	(-0.70)	(-1.04)

Table 21: Six-Month/Six-Month Strategy: Two-Dimensional Sort on Size and MT: 1982-2005

At the beginning of month t, I sort stocks independently into three groups of the MT measure, three groups of market capitalization at the end of month t-1, and quintiles of cumulative returns over the six-month perioud up to the end of month t-1. Following the six-month-holding/six-month-formation strategy of Jegadeesh and Titman (2001), I hold these three-dimensionally sorted portfolios for six months. Panel A reports the average monthly returns of the portfolios and Panel B reports the comparisons of momentum profits across the size-MT groups. Average size and average MT are measured in decile ranks. Specifically, I assign deciles ranks of size and MT to the stocks in each cross-section, where 1 is assigned to the bottom deicle and 10 to the top decile. I then calculate time series averages of the cross sectional mean ranks of size and MT for each size-MT group.

Panel A: Momentum Profits Across Size-MT groups

Size	MT	Loser	2	3	4	Winner	W-L	t-stat	Ave.Size	Ave.MT
Small	Low	0.65	1.15	1.13	1.32	1.64	0.99	(3.52)	2.17	2.07
Small	Med	0.85	1.24	1.33	1.49	1.78	0.93	(3.67)	2.28	5.51
Small	High	0.36	1.05	1.22	1.40	1.80	1.44	(5.90)	2.18	9.01
Med.	Low	0.82	1.20	1.26	1.20	1.51	0.69	(2.44)	5.48	2.20
Med.	Med	0.78	1.25	1.32	1.39	1.70	0.92	(3.39)	5.54	5.51
Med.	High	0.62	1.05	1.21	1.31	1.69	1.07	(3.72)	5.48	8.79
Big	Low	1.03	1.26	1.26	1.27	1.41	0.37	(1.25)	8.81	2.35
Big	Med	0.96	1.25	1.34	1.31	1.54	0.58	(1.94)	8.86	5.49
Big	High	0.79	1.19	1.24	1.23	1.60	0.81	(2.48)	8.70	8.54

Panel B: Comparisons of Momentum Profits

		Size Level				
		Small	Med.	Big	S-B	t-stat
	Low	0.99	0.69	0.37	0.62	(3.60)
MT level	Med.	0.93	0.92	0.58	0.35	(1.89)
	High	1.44	1.07	0.81	0.63	(2.99)
	H-L	0.45	0.38	0.44		
	t-stat	(2.73)	(2.38)	(2.22)		

Table 22: Six-Month/Six-Month Strategy: Two-Dimensional Sort on the Book-to-Market Ratio and MT: 1982-2005

This table presents momentum profits across BM-MT groups. At the beginning of month t, I independently sort stocks into three groups of the MT measures, three groups of book-to-market ratios, and quintiles of cumulative returns over the six-month period up to the end of month t-1. Following the six-month holding/six-month formation strategy of Jegadeesh and Titman (2001), I hold these three-dimensionally sorted portfolios for six months. Panel A reports the average monthly returns of the portfolios and Panel B reports the comparisons of momentum profits across the BM-MT groups. Average book-to-market ratio and average MT are measured in decile ranks. Specifically, I assign deciles ranks of the book-to-market ratio and MT to the stocks in each cross-section, where 1 is assigned to the bottom deicle and 10 to the top decile. I then calculate time series averages of the cross-sectional mean ranks of the book-to-market ratio and MT for each BM-MT group. Book-to-market ratio is calculated by dividing the summation of fiscal year-end book equity and deferred tax by market equity. I then apply the book-to-market ratio at the fiscal year end of year t to the one year period starting from July of year t+1.

Panel A: Momentum Profits Across BM-MT groups

BM	MT	Loser	2	3	4	Winner	W-L	t-stat	Ave.BM	Ave.MT
Low	Low	0.63	1.04	1.05	1.11	1.28	0.65	(2.19)	2.25	2.19
Low	Med	0.62	0.94	1.16	1.29	1.57	0.95	(3.24)	2.27	5.60
Low	High	0.15	0.64	0.93	1.16	1.53	1.39	(4.73)	2.12	8.96
Med.	Low	1.07	1.26	1.32	1.28	1.66	0.59	(2.02)	5.53	2.26
Med.	Med	1.04	1.33	1.38	1.35	1.67	0.64	(2.33)	5.52	5.54
Med.	High	0.79	1.10	1.19	1.28	1.60	0.82	(2.83)	5.45	8.76
High	Low	1.08	1.39	1.36	1.38	1.54	0.46	(1.68)	8.84	2.24
High	Med	1.24	1.46	1.44	1.52	1.64	0.41	(1.57)	8.76	5.53
High	High	1.03	1.46	1.46	1.47	1.91	0.88	(2.95)	8.78	8.72

Panel B: Comparisons of Momentum Profits

		BM Level				
		Low	Med.	High	L-H	t-stat
	Low	0.65	0.59	0.46	0.19	(0.93)
MT level	Med.	0.95	0.64	0.41	0.54	(2.54)
	High	1.39	0.82	0.88	0.51	(2.22)
	H-L	0.74	0.23	0.41		
	t-stat	(4.00)	(1.28)	(2.02)		

Table 23: Six-Month/Six-Month Strategy: Two-Dimensional Sort on Turnover and MT: 1982-2005

This table presents momentum profits across turnover-MT groups. At the beginning of month t, I independently sort stocks into three groups of the MT measures, three groups of turnovers of month t-1, and quintiles of cumulative returns over the six-month period up to the end of month t-1. Following the six-month holding/six-month formation strategy of Jegadeesh and Titman (2001), I hold these three-dimensionally sorted portfolios for six months. Panel A reports the average monthly returns of the portfolios and Panel B reports the comparisons of momentum profits across the turnover-MT groups. Average turnover and average MT are measured in decile ranks. Specifically, I assign deciles ranks of turnover and MT to the stocks in each cross-section, where 1 is assigned to the bottom deicle and 10 to the top decile. I then calculate time series averages of the cross-sectional mean ranks of turnover and MT for each turnover-MT group. Turnovers are demeaned by the cross sectional average turnovers of NYSE/AMEX or NASDAQ stocks according to the market where the firms is listed.

Panel A: Momentum Profits across Turnover-MT groups

TO	MT	Loser	2	3	4	Winner	W-L	t-stat	Ave.TO	Ave.MT
Low	Low	0.85	1.20	1.22	1.31	1.45	0.60	(2.59)	2.21	2.24
Low	Med	1.00	1.26	1.35	1.41	1.59	0.59	(2.81)	2.23	5.47
Low	High	0.98	1.28	1.37	1.47	1.70	0.72	(3.36)	2.14	8.64
Med.	Low	0.92	1.27	1.25	1.31	1.54	0.61	(2.49)	5.49	2.24
Med.	Med	0.97	1.31	1.36	1.44	1.64	0.67	(2.77)	5.46	5.48
Med.	High	0.72	1.26	1.30	1.33	1.66	0.93	(3.58)	5.56	8.67
High	Low	0.64	1.04	1.11	1.21	1.55	0.91	(2.81)	8.70	2.12
High	Med	0.63	1.07	1.28	1.32	1.73	1.09	(3.74)	8.71	5.53
High	High	0.20	0.78	0.98	1.17	1.69	1.49	(5.10)	8.92	8.97

Panel B: Comparisons of Momentum Profits

		Turnover Level				
		Low	Med.	High	H-L	t-stat
	Low	0.60	0.61	0.91	0.31	(1.64)
MT level	Med.	0.59	0.67	1.09	0.51	(2.85)
	High	0.72	0.93	1.49	0.77	(3.87)
	H-L	0.12	0.32	0.59		
	t-stat	(0.78)	(2.28)	(3.57)		

Table 24: Return Momentum Across Residual MT (ResMT1) Groups: 1982-2005

For each month t of the sample period, I run a cross-sectional regression of the MT measure on firm size (natural log of market capitalization) at the end of month t-1, BE/ME, and demeaned turnover of month t-1. Residual MT (ResMT1) are the residuals from these regressions. I sort stocks into three groups of residual MT and ten groups of past performance, and calculate profits of six-month formation/six-month holding strategy following Jegadeesh and Titman (2001) for each MT group. Specifically, at the beginning of month t, I independently sort stocks into three groups of the ResMT1 measures and deciles of cumulative stock returns during the six-month period up to the end of month t-1. I then hold these portfolios for six months from the beginning of month t and report average portfolio returns in Panel A. Panel B reports the results of Fama-French three-factor model of the momentum profits of the low, medium and high residual MT groups. The t-statistics are calculated with Newey-West robust standard errors.

Panel A: Momentum Profits Across Residual MT Terciles - ResMT1

ResMT1	Loser	2	3	4	5	6	7	8	9	Winner	Winner - Loser	t-stat
Low	0.74	0.97	1.22	1.26	1.27	1.27	1.25	1.32	1.37	1.67	0.93	(2.42)
Medium	0.63	1.00	1.17	1.28	1.33	1.33	1.36	1.42	1.50	1.86	1.22	(3.52)
High	0.29	0.91	1.00	1.16	1.22	1.24	1.28	1.31	1.45	1.79	1.50	(4.17)
High - Low											0.57	(3.24)

Panel B: Fama-French 3 factor Regressions of Momentum Profits - ResMT1

ResMT1	Intercept	MKT	SMB	HML
Low	1.12	-0.35	0.46	-0.11
	(3.05)	(-3.22)	(1.81)	(-0.42)
Medium	1.42	-0.26	0.27	-0.09
	(3.75)	(-2.36)	(1.20)	(-0.40)
High	1.67	-0.18	0.32	-0.16
	(4.19)	(-1.73)	(1.51)	(-0.68)
High - Low	0.48	0.17	-0.13	-0.05
	(2.87)	(3.45)	(-1.61)	(-0.54)

Table 25: Return Momentum Across Residual MT (ResMT2) Groups: 1982-2005

For each month t of the sample period, I run a cross-sectional regression of the MT measure on firm size (natural log of market capitalization) at the end of month t-1, BE/ME, demeaned turnover of month t-1, residual analyst coverage of month t-1, return volatility in the 25 trading days up to month t-1, and firm age up to month t-1. The ResMT2 measures are the residuals from these regressions. I sort stocks into three groups of ResMT2 and ten groups of past performance, and calculate profits of six-month formation/six-month holding strategy following Jegadeesh and Titman (2001) for each MT group. Specifically, at the beginning of month t, I independently sort stocks into three groups of the ResMT2 measures and deciles of cumulative stock returns during the six-month period up to the end of month t-1. I then hold these portfolios for six months from the beginning of month t and report average portfolio returns in Panel A. Panel B reports the results of Fama-French three-factor model of the momentum profits of the low, medium and high residual MT groups. The t-statistics are calculated with Newey-West robust standard errors.

Panel A: Momentum Profits Across Residual MT Terciles - ResMT2

ResMT2	Loser	2	3	4	5	6	7	8	9	Winner	Winner - Loser	t-stat
Low	0.73	0.94	1.20	1.26	1.26	1.27	1.24	1.32	1.39	1.69	0.96	(2.52)
Medium	0.61	1.02	1.15	1.28	1.33	1.33	1.36	1.41	1.49	1.86	1.25	(3.51)
High	0.32	0.92	1.04	1.18	1.22	1.25	1.29	1.32	1.44	1.77	1.45	(4.02)
High - Low											0.49	(2.89)

Panel B: Fama-French 3 factor Regressions of Momentum Profits - ResMT2

ResMT2	Intercept	MKT	SMB	HML
Low	1.21	-0.33	0.41	-0.11
	(3.12)	(-3.06)	(1.65)	(-0.39)
Medium	1.48	-0.29	0.30	-0.12
	(3.88)	(-2.69)	(1.31)	(-0.54)
High	1.63	-0.19	0.35	-0.16
	(4.07)	(-1.79)	(1.62)	(-0.67)
High - Low	0.42	0.14	-0.06	-0.05
	(2.52)	(2.68)	(-0.78)	(-0.58)

Table 26: Return Momentum Across MTWO Groups: 1982-2005

I sort stocks into three groups of the MTWO measure and ten groups of past performance, and calculate profits of six-month-formation/six-month-holding strategy following Jegadeesh and Titman (2001) for each MTWO group. Specifically, at the beginning of month t, I independently sort stocks into three groups of the MTWO measures and deciles of cumulative stock returns during the six-month period up to the end of month t-1. I then hold these portfolios for six months from the beginning of month t and report average portfolio returns in Panel A. Panel B reports the results of Fama-French three-factor model of the momentum profits of the low, medium and high MTWO groups. The t-statistics are calculated with Newey-West robust standard errors.

Panel A: Momentum Profits Across MTWO Terciles

MT Level	Loser	2	3	4	5	6	7	8	9	Winner	Winner - Loser	t-stat
Low	0.65	1.01	1.23	1.26	1.29	1.26	1.28	1.32	1.43	1.72	1.06	(2.93)
Medium	0.38	1.04	1.16	1.19	1.25	1.30	1.34	1.41	1.52	1.75	1.36	(3.62)
High	0.31	0.91	1.00	1.23	1.24	1.27	1.30	1.34	1.46	1.86	1.55	(4.57)
High - Low											0.49	(2.94)

Panel B: Fama-French 3 factor Regressions of Momentum Profits

MT Level	Intercept	MKT	SMB	HML
Low	1.30	-0.31	0.29	-0.08
	(3.43)	(-2.84)	(1.22)	(-0.32)
Medium	1.58	-0.31	0.38	-0.07
	(4.05)	(-2.63)	(1.76)	(-0.26)
High	1.74	-0.19	0.24	-0.19
	(4.70)	(-2.01)	(1.13)	(-0.86)
High - Low	0.45	0.12	-0.06	-0.10
	(2.76)	(2.97)	(-0.81)	(-1.08)

Table 27: Earnings Revision Across MT-Momentum Portfolios: 1982-2005

This table reports earnings revisions during the one-year post-ranking period across MT-Momentum portfolios. Earnings Revision in month t is the change of the mean earnings forecasts from month t-1 to month t, adjusted by stock price at the end of month t-1. At the beginning of month t, stocks are sorted into quintiles of the MT measures and past six months' cumulative stock returns (P5 refers to extreme winner quintile and P1 refers to extreme loser quintile). Next, I report in Panel A the average earnings revisions during the twelve months after portfolio formation in each portfolio and the differences between winners and losers portfolios within MT quintiles. The t-statistics of the differences are reported in parenthesis. Panel B compares the differences in earnings revision between winners and losers portfolios of the top and the bottom MT quintiles. The empirical method is the same as the rolling momentum strategy except that I calculate average monthly earnings revisions rather than stock returns.

Panel A: Post Formation Analysts Revision of MT-Momentum Portfolios													
		Number of Months after Portfolio Formation											
MT	PastRet.	1	2	3	4	5	6	7	8	9	10	11	12
Low	P1	-0.0252	-0.0211	-0.0174	-0.0363	-0.0228	-0.0182	-0.0639	-0.0431	-0.0476	-0.0555	-0.0912	-0.0390
Low	P5	-0.0010	-0.0051	-0.0065	-0.0078	-0.0036	-0.0036	-0.0041	-0.0122	-0.0145	-0.0241	-0.0115	-0.0157
(1)	P5-P1	0.0242	0.0160	0.0110	0.0284	0.0192	0.0146	0.0598	0.0310	0.0331	0.0313	0.0798	0.0233
	t-stat	(2.84)	(2.17)	(1.59)	(1.65)	(3.47)	(3.21)	(2.23)	(1.56)	(1.58)	(1.20)	(1.63)	(1.15)
2	P1	-0.0335	-0.0537	-0.0664	-0.0522	-0.0834	-0.0679	-0.0635	-0.0470	-0.1108	-0.0525	-0.0737	-0.0626
2	P5	-0.0192	-0.0117	-0.0095	-0.0173	-0.0198	-0.0166	-0.0054	-0.0018	-0.0019	-0.0111	-0.0156	-0.0119
(2)	P5-P1	0.0142	0.0420	0.0569	0.0349	0.0636	0.0513	0.0581	0.0451	0.1089	0.0414	0.0581	0.0508
	t-stat	(0.71)	(1.66)	(2.58)	(1.64)	(2.14)	(1.89)	(2.73)	(2.22)	(2.18)	(1.89)	(2.06)	(2.03)
3	P1	-0.0171	-0.0129	-0.0180	-0.0137	-0.0157	-0.0168	-0.0046	-0.0203	-0.0203	-0.0029	0.0037	-0.0155
3	P5	-0.0039	-0.0102	-0.0072	-0.0130	-0.0114	-0.0076	-0.0125	-0.0047	-0.0114	-0.0037	-0.0090	0.0062
(3)	P5-P1	0.0133	0.0026	0.0108	0.0008	0.0043	0.0092	-0.0079	0.0156	0.0089	-0.0008	-0.0127	0.0216
	t-stat	(1.55)	(0.26)	(0.96)	(0.06)	(0.38)	(0.98)	(-0.61)	(0.98)	(0.60)	(-0.06)	(-0.75)	(1.19)
4	P1	-0.0111	-0.0161	-0.0211	-0.0224	-0.0198	-0.0377	-0.0392	-0.0252	-0.0214	-0.0419	-0.0325	-0.0187
4	P5	0.0000	0.0004	0.0002	-0.0001	0.0001	0.0002	-0.0004	-0.0019	-0.0022	-0.0023	-0.0004	-0.0034
(4)	P5-P1	0.0111	0.0165	0.0213	0.0223	0.0200	0.0379	0.0389	0.0233	0.0192	0.0396	0.0321	0.0154
	t-stat	(3.34)	(2.31)	(2.44)	(2.99)	(3.44)	(2.90)	(3.17)	(2.99)	(3.19)	(2.54)	(2.64)	(2.76)
High	P1	-0.0221	-0.0164	-0.0206	-0.0271	-0.0235	-0.0265	-0.0280	-0.0361	-0.0320	-0.0386	-0.0468	-0.0579
High	P5	-0.0001	-0.0004	-0.0022	-0.0027	-0.0020	-0.0020	-0.0014	-0.0038	-0.0029	-0.0027	-0.0051	-0.0086
(5)	P5-P1	0.0220	0.0161	0.0184	0.0244	0.0215	0.0245	0.0267	0.0323	0.0291	0.0359	0.0416	0.0493
	t-stat	(3.77)	(3.66)	(3.10)	(3.47)	(4.37)	(4.29)	(3.86)	(2.75)	(3.00)	(3.50)	(2.68)	(2.42)
Panel B: Comparison of Differences in Analyst Forecasts													
(5) - (1)		-0.0022	0.0001	0.0074	-0.0040	0.0023	0.0099	-0.0332	0.0013	-0.0041	0.0046	-0.0381	0.0260
t-stat		(-0.21)	(0.01)	(0.82)	(-0.22)	(0.31)	(1.35)	(-1.19)	(0.06)	(-0.18)	(0.16)	(-0.74)	(0.90)

Table 28: Long-Term Reversals in Momentum Profits Across MT Levels

At the beginning of month t, I independently sort stocks into quintiles of the MT measures and past six months' cumulative stock returns. I then calculate within each MT quintile the cumulative momentum profits (top past-return quintile minus bottom past-return quintile) up to each month during the three-year post-ranking period. Returns are measured in the scale of percentage.

	Number of Months After Portfolio Formation												
MT	3	6	9	12	15	18	21	24	27	30	33	36	36-12
Low	2.17	4.34	6.69	7.14	5.21	4.13	4.29	3.92	2.70	2.41	3.42	3.70	-3.44
2	1.67	4.15	7.09	7.58	6.45	6.07	6.33	6.13	3.94	3.38	4.01	3.79	-3.79
3	1.77	4.72	7.15	7.78	6.98	6.54	6.63	5.91	4.32	3.98	4.24	4.03	-3.75
4	2.53	5.80	8.86	9.68	8.68	8.26	8.55	7.62	5.58	4.81	5.35	4.85	-4.83
High	3.47	7.39	10.08	11.18	10.27	9.14	9.45	8.70	6.97	6.09	5.41	4.82	-6.36

Table 29: Six-Month/Six-Month Strategy: Two-Dimensional Sort on FIT and MT: 1982-2005

This table presents momentum profits across FIT-MT groups. At the beginning of month t, I independently sort stocks into three groups of the MT measures, three groups of one-quarter lag FIT measures, and quintiles of cumulative returns over the six-month period up to the end of month t-1. Following the six-month holding/six-month formation strategy of Jegadeesh and Titman (2001), I hold these three-dimensionally sorted portfolios for six months. Panel A reports the average monthly returns of the portfolios and Panel B reports the comparisons of momentum profits across the FIT-MT groups.

Panel A: Momentum Profits across FIT-Inst.Ownership groups

FIT	MT	Loser	2	3	4	Winner	W - L	t-stat
Low	Low	0.74	1.08	1.07	1.07	1.36	0.62	(2.68)
Low	Med	0.76	1.07	1.18	1.19	1.59	0.83	(3.46)
Low	High	0.58	1.01	1.15	1.22	1.78	1.21	(5.06)
2	Low	1.15	1.33	1.35	1.27	1.46	0.32	(1.56)
2	Med	1.10	1.34	1.46	1.36	1.52	0.42	(2.16)
2	High	0.96	1.35	1.42	1.40	1.55	0.59	(2.80)
High	Low	1.27	1.31	1.32	1.32	1.47	0.20	(1.08)
High	Med	1.23	1.44	1.41	1.43	1.58	0.35	(2.00)
High	High	1.22	1.44	1.48	1.48	1.76	0.53	(2.90)

Panel B: Matrix of Momentum Profits

		FIT Level				
		Low	Med.	High	L-H	t-stat
	Low	0.62	0.32	0.20	0.42	(2.42)
MT Level	Med.	0.83	0.42	0.35	0.48	(2.65)
	High	1.21	0.59	0.53	0.67	(3.89)
	H-L	0.58	0.27	0.33		
	t-stat	(3.27)	(1.77)	(2.22)		

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